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A review and an analysis of the residential electric load curve models

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ABSTRACT

Due to the growth of electric end-uses, the management of the variations in time of the electric power demand has become essential, especially in the residential sector. According to this issue, the anticipation of the power demand is of great interest. This implies a better knowledge of the electric load curve of the household stock. Papers about understanding and forecasting energy demand are numerous but studies on building's load curves are rare. In this paper we propose a cross analysis of some existing methods capable of building up a residential electric load curve. Two main types of load curve models have been identified in the literature: top-down and bottom-up methods. Even if the review presents two existing top-down approaches, the authors focused the further analysis on bottom-up models. For each of them we first identify its functional characteristics: finality and scope, input data required, output format, modeled appliances and end-uses covered, generation of the diversity and validation of the model. Secondly, we establish a bloc diagram representing its architecture with focus on the mathematical model chosen. Finally, the authors list the limits of the model in view of the criteria needed to build up an ideal, bottom-up and technically explicit load curve model for the residential sector.

A cross reading of the different methodologies is proposed through a global table that characterizes and sums up the analyzed models. Moreover, a graphical representation of the models studied is proposed, according to three criteria (range of application, modelling of the diversity, time scale accuracy) that allows us to compare them "at a glance". To conclude, an identification of the gaps among existing models is proposed. It consists of listing the end-uses, the appliances and other behavioural correlations which may affect the load curve and that are not included in the reviewed methodologies and need further research.

Contents

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1. Introduction

Modelling the electricity consumption of the residential sector is not a recent research topic. For a few decades authors have published their methods developed to anticipate the temporal evolution of the electric energy demand with different time and space scale considerations. Among the motivations for developing such a model, the main one is the need of a tool to better predict, quantify and plan the future requirements in terms of power plants. Other reasons are the electric network control and management or the impacts of various evolution scenarii that focus on technical, demographic, behavioural or economical aspect.

For such purposes the authors generally focused on the annual electric energy demand and the chosen methodologies are different depending on the finality, the scope, the input data and the output format of each model.

Historically, the methods have been divided into two categories: top-down and bottom-up approaches. Swan and Ugursal indicate that this classification "is with reference to the hierarchal position of data inputs as compared to the housing sector as a whole" [1]. Models operate according to one of the processes represented in Fig. 1. However, some authors tried to benefit from the advantages of both approaches and thus develop hybrid models.

Swan and Ugursal [1] have classified the domestic electricity demand models of the literature with regard to the method used. They established a finer segmentation of the available methods than the simple differentiation between top-down and bottom-up methods. In this paper, we carried out a similar, global and transverse analysis of the methodologies for modelling the electric power demand.

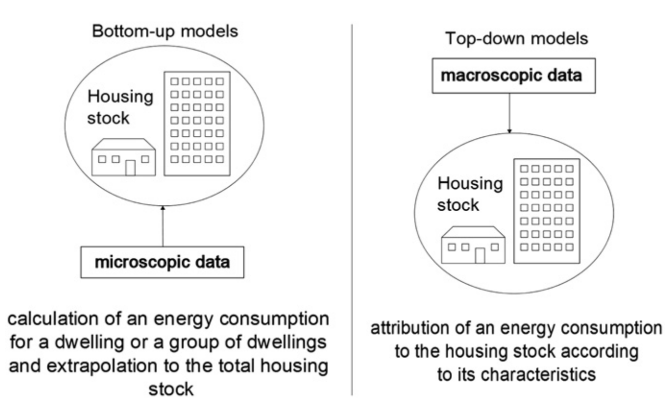

Fig. 1. Top-down vs bottom-up models.

The power demand issue is a more recent research topic than the study of electric energy consumption. However, many references exploring the load curve research field have been published since the 1940s: Hamilton [2,3] and Bary [4] respectively focused on the properties of aggregated load curves and on the mathematical relationships between load curve characteristic factors (coincidence factor, load factor). In Europe, UNIPEDE [5] published the first load curve manual to clarify the load curve concepts and terminology. Rehberg [6] proposed a publication about the study of the residential load curve. In the United States, the Association of Edison Illuminating Companies (AEIC) [7–9] published several versions of the procedures to carry out load curve surveys.

In fact power demand is more complicated to predict than energy demand because of its random nature and its acute fluctuating aspect. On top of that, even if customers can have the same general characteristics (e.g. two domestic customers with the same household size, type of dwelling, building characteristics, appliances ownership, etc.) there is every chance that their corresponding power demand, so their load curves for selected days, are completely different. Diversity that represents both the non-coincidence in energy use and an unlimited variety of customers' characteristics is responsible for this effect.

The influence of the human behaviour on the domestic power demand is so important that there is every chance for instance that two households with the same daily energy consumption will not show a similar load curve. That is the reason why modelling the power demand in a specific area for a specified target is also an hard task.

The power demand issue was explored to ensure the safety of electricity supply, to better predict the peak power demand, to optimize the network control techniques and to analyze the impact of Demand Side Management (DSM) strategies or the modification of the network load flows after integration of renewable energy sources.

The aim of this paper was the establishment of a new and improved classification of the residential load curve models described in the recent publications. This segmentation can be seen in Fig. 2.

We decided to analyze these models with reference to an ideal and to our knowledge of non-existing model. To our opinion such an ideal model should present the following characteristics:

- it has to be parametric in order to simulate various scenarii;
- it has to be technically explicit i. e. the different specificities of the simulated elements (equipments, buildings, etc.) must specifically impact the load curve calculations and results;

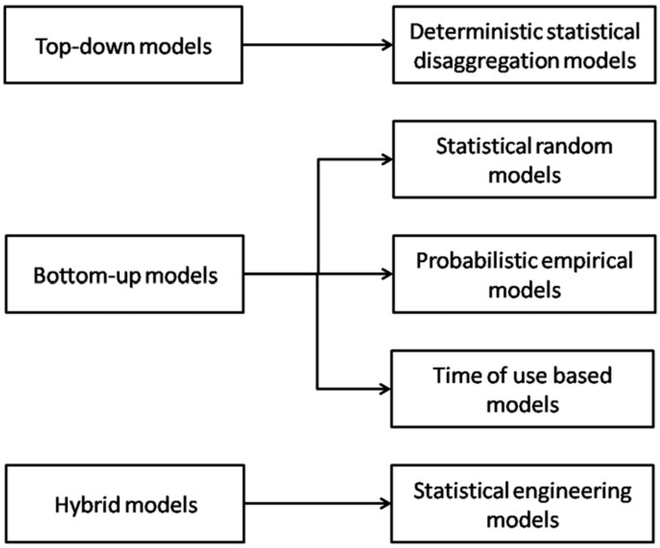

Fig. 2. Proposed classification of the load curve models.

- it has to be evolutive, i. e. new elements can be introduced in the model so as to be simulated;
- it has to be aggregative so that results can be obtained at different levels (household, area, city, region, etc.);
- all domestic end-uses must be considered in the load curve calculations: Heating, Ventilation and Air Conditionning (HVAC), Domestic Hot Water (DHW) and specific electricity appliances.

According to the manner diversity is gotten, we define five types of models:

- deterministic statistical disaggregation model: this approach consists of disaggregating measured load profiles to identify various appliances. Diversity is not modelled at all because it is embedded, in a deterministic way, in the measured data;
- statistical random model: in such a model, the reconstitution of the diversity makes use of statistical data. To generate variations for a given scenario, a random procedure is applicated;
- probabilistic empirical model: from real collected data concerning, among other things, domestic habits of people, probabilistic procedures are defined and applied to generate a diversity of results;
- Time of use (TOU) based model: diversity is constructed thanks to data coming from time of use surveys (real and precise data concerning the behaviour of people);
- statistical engineering model: in this case, the diversity is partly embedded in the measured data that serve as input (dwelling characteristics, weather data, penetration rates, etc.). On top of that, diversity is embedded in the statistical coefficients that adjust the original results. These coefficients are calculated with the help of measured load curves and socio-economic data.

To carry out our analysis, we decided to follow a generic reading process for each model. We will focus on a series of criteria in order to build a standardized ID for each approach. This will help us to set the cross reading table at the end of this paper, all models considered.

In Section 2, after a short introduction about the top-down approach, the authors review two of them that use a deterministic statistical disaggregation method. Section 3 first provides a short description of the bottom-up methodology, then an analysis of the corresponding models. These methodologies are classified according to the proposed segmentation. In the following, Section 4 exposes a model which is not sortable into the two main families: it is an hybrid method. At the end of this paper, a comparison of all methods, following a cross analysis procedure, is carried out. The main properties of the models are put together into a synthetic table and a graphical representation using three criteria is drawn.

2. Top-down models

2.1. Introduction

Top-down methodologies consider situation on a whole (making use of national energy statistics for instance) and try to attribute an electricity consumption to the studied household stock with regard to its characteristics. The input data for this type of model are very general information such as:

- Gross Domestic Product (GDP),
- unemployment rate,
- present statistics on the targeted population with possibly predicted evolution,
- appliance saturation rates, etc.

Generally these methodologies consist of a mathematical identification of the past and present electricity demand for a specified area. On this basis, the model may be used to generate trend evolutions: that can be well predicted by this type of model. The advantages of such a method is its simplicity, the use of generally well available and aggregated data and the possibility to calibrate the simulation tool with real electricity consumption values. Yet these models are unable to simulate the impacts of technical breaks or the appearance of new end-uses which have not been measured.

2.2. Deterministic statistical disaggregation models

In this section we present two methodologies whose aim is the analysis of residential load curve. In fact, total load curve (i. e. the aggregated power demand of a dwelling, all end-uses being considered) measurements are used as input data and the models try then to differentiate the individual contribution of the observed end-uses. This work corresponds to the load curve analysis and it makes use of mathematical techniques such as regression, statistical or econometric methods. In this approach, the authors try to explain the domestic electric power demand (dependent variable) with the help of some various and independent variables.

2.2.1. Aigner et al.'s model

Aigner et al. present in [10] the methodology they developed in order to get the hourly load curves of selected domestic end-uses for households located in areas next to Los Angeles. This analysis technique is in fact the same that Parti & Parti [11] developed for the domestic energy consumption analysis: this is called Conditional Demand Analysis (often mentioned as CDA). Aigner et al. reuse the same mathematical development made in [11] (the base CDA) but the authors improved it so that the variable which is explained becomes the hourly electric power demand.

As input data, the authors used on the one hand total load curves measured at a 15 min time step and on the other hand appliance penetration rates for the selected equipments.

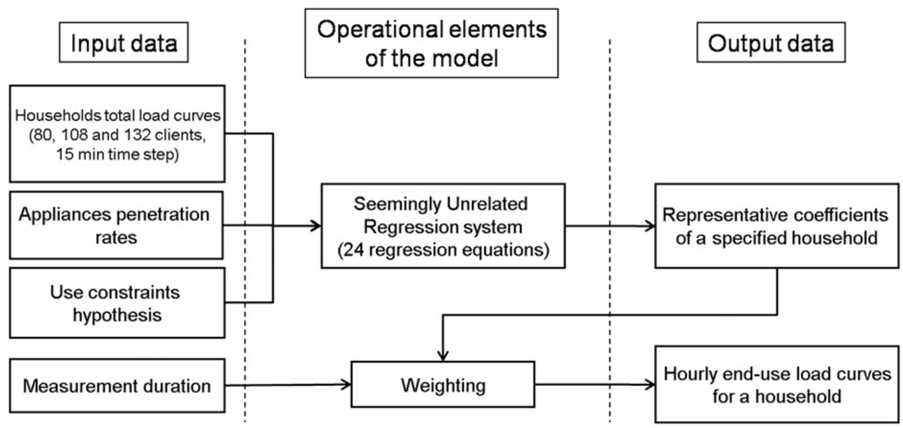

Fig. 3. Bloc diagram of Aigner et al.'s model [10].

CDA model uses 24 regression equations (one equation for each hour of a day). Each mathematical relation tries to determine the hourly variation of the customers group's load curve compared to the mean daily power demand value.[1] The variables which explain the power demand are:

- the desired temperature in the home (two scalar variables): they are set with taking into account the outdoor temperature of the geographical area[2];
- the size of the dwelling (three scalar variables informing the number of rooms);
- nine dummy variables representing the presence or absence of the observed appliances[3] in a specified household (binary variables).

Running the regression model over the 24 h of a day without taking into consideration relationships between hours (notably in terms of consumption habits) may give incoherent results. That is the reason why the authors include in their method some simplifications and apply use restrictions. These constitute what the authors call a Seemingly Unrelated Regression system.

Moreover the authors introduce in the mathematical model an indicator to differentiate the power demand according to the house typology: detached house or flat. The functional architecture of Aigner's model is shown in Fig. 3.

Aigner et al. present in [10] the results obtained when each regression equation is solved separately with three different mathematical techniques:

- ordinary least square method without use restrictions;
- ordinary least square method with use restrictions;
- generalized least square method with use restrictions.

The obtained results with the three calculation ways are in the same range. The authors notice that the restriction use is useful in order to improve the real aspect of the daily load curves. Yet there is no comparison in the paper of the obtained end-uses daily load curves with other measurements for each appliance. So the level of the regression results are questionable because of this absence of validation.

To conclude with this model, we can say that Aigner et al. propose a way to get hourly load curve for some electric appliances in a sample of households compared to the direct metering of each equipment. This model version can be improved if input data concerning the real daily use of the domestic appliances is used. In this way, uses of equipments can be defined more accurately. Nevertheless the model is limited when considering the accuracy of the results. There is no distinction in terms of unitary load profile between the same type of electric device and the use scenarii between the households. Another limit of the model is its disability to supply the load curve of appliances which are in a large majority of dwellings: the refrigerator is the best example. On the other hand, CDA technique presents a good ability to identify the load curve of appliances with an high energy consumption.

2.2.2. Bartels et al.'s model

Bartels et al. present in [12] the load curve model called DELMOD they develop on the basis of the CDA technique. In fact, CDA is part of its functional procedure but it is not the only one as Fig. 4 shows.

The aim of the authors was to obtain a tool able to simulate the impact of various scenarii on the regional power demand of the household stock.

DELMOD is made of two modules:

- DELMOD B (base module) calculates the load curve of the residential sector for a mean working day and a specified month.
- DELMOD W (weather module) quantifies the climatic influence on the power demand and modifies the results of the base module.

Results of this model are hourly load curves.

As input data, this method requires much more information as Aigner et al.'s model. In fact, on top of measurements of total load curve (400 consumers, 15 min time step) and information concerning the saturation rates of appliances (which are the same type of input data as last model), DELMOD makes use of weather data (outdoor temperature knowledge over the load curve measurement period), socio-economical and technical evolution scenarii (expressed through the growth or the decline of economical, demographical and social indexes). This feature enables the use of DELMOD so as to do demand forecasts.

In this model, the authors selected nine different appliances.[4] Another variable was included in the model so as to take into

[1] This last figure is calculated over an entire month.

[2] The three measured samples correspond to so many climatic zones.

[3] Central air conditioner, room air conditioner, water heater, dishwasher, washing machine, tumble dryer, range, freezer and swimming pool pump.

[4] Air conditioner, freezer, automatic defrost fridge, oven, dishwasher, tumble dryer, main and/or secondary heater, water heater (off peak and main tariff) and pool pump.

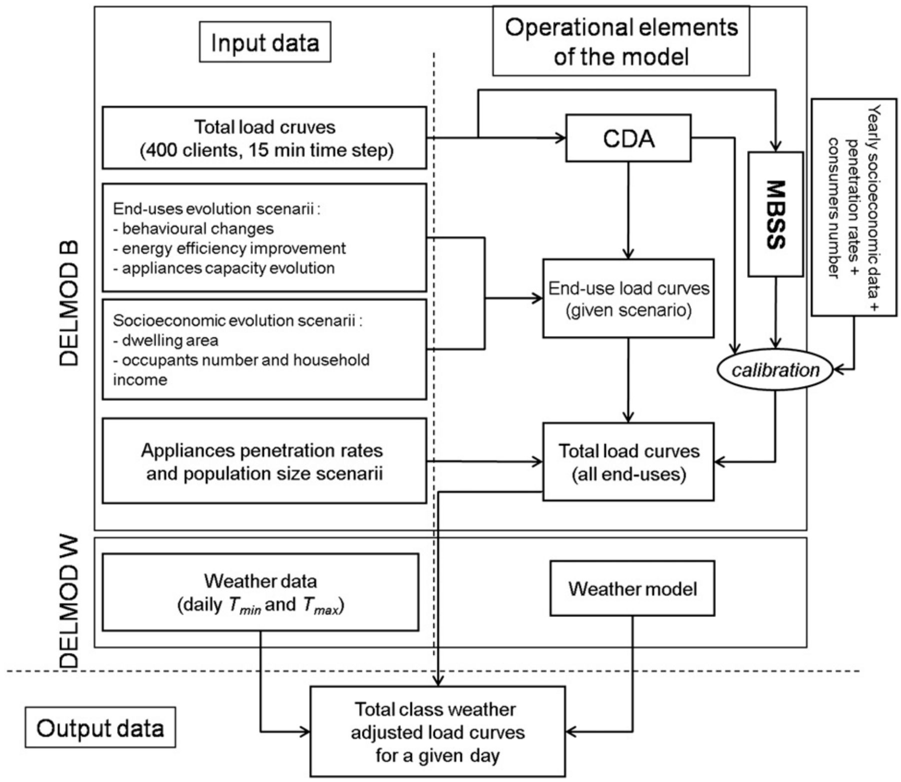

Fig. 4. Bloc diagram of Bartels et al.'s model [12].

consideration the domestic appliances with a large power demand. The remaining power corresponds to the in-the-model unspecified appliances.

Some coefficients are used in order to take into account the evolution of the technical and/or behavioural aspect which may affect the load curve of each end-use. The capacity and the efficiency of the appliances are the selected factors. Concerning the sociological and economical evolutions three influences are used: dwelling size, number of occupants per household and income.

So in order to take into consideration the meteorological influences, Bartels et al. introduce in the model the minimal and maximal daily outdoor temperature of the considered area (New South Wales, Australia).

From these different sources of information various scenarii can be established. All what concerns the non weather influences constitutes evolution trends which are constructed in two modules of DELMOD B. The weather scenarii are built in DELMOD W. There are temperature profiles for the simulation period constructed from the measured chronicle on which deviations around the calculated mean daily temperature are implemented.

Bartels et al. construct the hourly load curves of the selected end-uses with help of the CDA technique whose results are calibrated using the Model Based Statistical Sampling (MBSS) method – developed in [13] – enabling then to obtain better results than those from the "simple" Conditional Demand Analysis. End-uses load curves are then obtained for two types of day: with or without evening shopping.

Bartels et al. simulate the day when the peak load has been reached (the "peak day") and analyze the results of DELMOD. Total load curves for customers were calculated after aggregation of their different end-uses. Apparently the model enables a good representation of the load curve for this day. Other comparisons were made for a working day of each month of the year. In this case, DELMOD provides not so fine results as for the peak day. As explanation for this observation, the authors say that the considered end-uses are much more weather dependent in cold months.

DELMOD is a load curve model which can be used for power demand forecasts what constitutes a good improvement comparing with the CDA technique. Various evolution sources can be then taken into account. Yet the model suffers the disadvantages of the method developed by Aigner et al.: end-uses owned by a majority of households cannot be affected with a corresponding load curve. Moreover although the hourly power demand for the heating system[5] is calculated by the model, there is no differentiation in terms of thermal characterization of the envelope of the dwellings in the simulated area. Finally, the results of DELMOD have been compared on an aggregated basis. That is to say that end-use load curves have not been validated individually and thus do not have any proven validity for industrial use (e.g. impact after retrofiting a dwelling).

3. Bottom-up models

3.1. Introduction

Bottom-up models compute electric demand for a few modelled households which are either representative of a larger space scale or simply target consumers. The unitary results are then extrapolated to obtain the electricity consumption for the entire studied geographical scale. Here the required input data can be:

- the individual consumption of the selected domestic appliances;
- their technical properties;

[5] This constitutes a singularity among the presented load curve models.

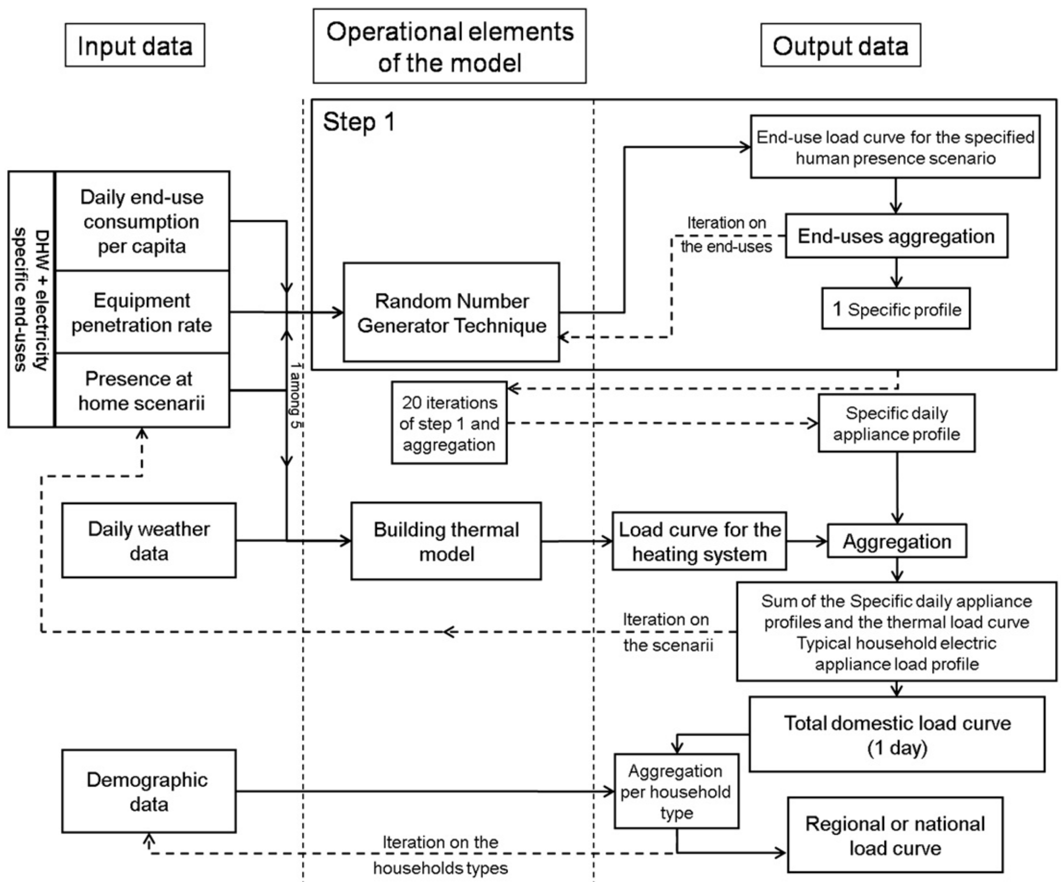

Fig. 5. Bloc diagram of Yao and Steemers's model [14].

- the geometrical and thermal properties of the modelled dwellings;
- weather information;
- electricity bills of households;
- human behaviour, etc.

This methodology presents the advantage of a high level of details because energy demand can be calculated for a couple of households and even for each end-use. With such data, energy demand evolutions may be more precisely quantified since the participation in the global demand of individual domestic appliances is known. Energy demand measurements are not absolutely necessary and thus it is possible to simulate and to obtain results for non-trend scenarii. Among other capabilities, this enables the simulation of the impact of technical breaks. Higher precision is correlated with higher complexity of the modelling and with the requirement of a large amount of input data.

In this section we present methodologies whose aim is the synthesis of residential load curve. With help of accurate data, the authors try to build up the load curve of households when considering a set of selected appliances and with applying a series of assumptions. On top of that, diversity affecting electricity consumption has to be generated by the model. Various methodologies exist to obtain it. To our opinion, some are relatively simple, other are well elaborated and complex. In the following, the models are classified thanks to the authors' adopted scale of complexity for the generation of diversity. The models appear according to a subjective and increasing complexity level of diversity.

3.2. *Statistical random model*

Yao and Steemers present in [14] the bottom-up model they built up. Called Simple Method of formulating Load Profile (SMLP), this method produces end-use load curves with consideration of various human occupation scenarii. SMLP was established in order to simulate the impact of the integration of decentralized energy production, especially with Photovoltaic (PV) modules, on the British electricity grid. The aim of this tool is notably to predict the peak load curves and to identify the network configurations when the system stability can be at fault. That is why the authors simulate the worst possible case that is to say that all appliances in each dwelling are supposed to run through each simulated day. Results of the method are total load curves at 1, 5, 15 or 30 min time steps. The model architecture is shown in Fig. 5.

Yao and Steemers make use of different input data:

- individual DHW profiles;
- per capita daily electricity consumption for each end-use;
- heating system energy consumption from simulation results of Yao et al.'s thermal model [15,16];
- statistical results from national population surveys;
- appliance saturation rates for a series of domestic electric devices;
- constructed occupation scenarii in the dwellings.

The (15) appliances taken into consideration are listed below: TV, VCR, fridge, freezer, fridge-freezer, hob, oven, kettle, micro-wave

oven, dishwasher, washing machine, tumble dryer, vacuum cleaner, iron and lighting.

In order to generate the total load curve (all end-uses considered) of a selected area and according to the parametrized simulation scenario, Yao and Steemers's model proceeds in three steps:

1. at the household level, generation of one daily load curve for a selected appliance and occupants' presence scenario: the start time is selected randomly with help of a Random Number Generator Technique (RNGT);
2. start time diversity is obtained when repeating previous step 20 times;
3. aggregation for the specified presence scenario of the daily load curves obtained at step 2: the resulting load curve is naturally smoother than the individual ones;
4. repetition of the steps 1–3 for each appliance according to the considered presence scenario;
5. repetition of the steps 1 to 4 for each presence scenario considered;
6. aggregation of previous total daily load curves according to the characteristics of the population area (composition of households, type of dwellings).

So as to validate their model, Yao and Steemers used a measured load curve coming from the data base of the UK Electricity Associate Load Research Team. The chosen load curve is a three-person household's, measured during a winter working day. The SMLP simulation to obtain a comparable load curve consisted of simulating a 100 household community, to calculate its load curve and to divide the result by 100 in order to get the load curve of the "mean" household.

The used method to give a validity to the model is very questionable because of the chosen compared things: individual and sample mean load curve are two very different elements.

To conclude, this model presents the advantage of the simplicity, the availability of the input data and its deeply bottom-up character (several aggregation steps are needed). Yet the occupation scenarii that are proposed by the authors seems to be very simple to represent the reality with a good fit. Moreover the introduction of the diversity is done with a pure mathematical procedure without considering for instance domestic habits. On top of that, the thermal model which is used corresponds to a one air-node building modelling which allows a limited daily regulation of the heating system in a home. There is no differentiation and/or no indication in terms of building envelope characteristics and appliance efficiency. That is the reason why technical evolution scenarii cannot be simulated with this model.

3.3. Probabilistic empirical models

3.3.1. Stokes's model

Stokes developed a model applicable to the domestic sector and presented in [17]. It is able to generate three types of aggregated load curves

1. 30 min demand profile for an average household (1st level),
2. 30 min demand profile for a specified dwelling (2nd level) and
3. 1 min demand profile for a selected domestic customer (3rd level)

with a fine spatial resolution that is the individual domestic appliance.

To get this gradual precision, the model is structured into three main modules; results of the level n serve as inputs of the level $n+1$. Fig. 6 schematically illustrates this architecture.

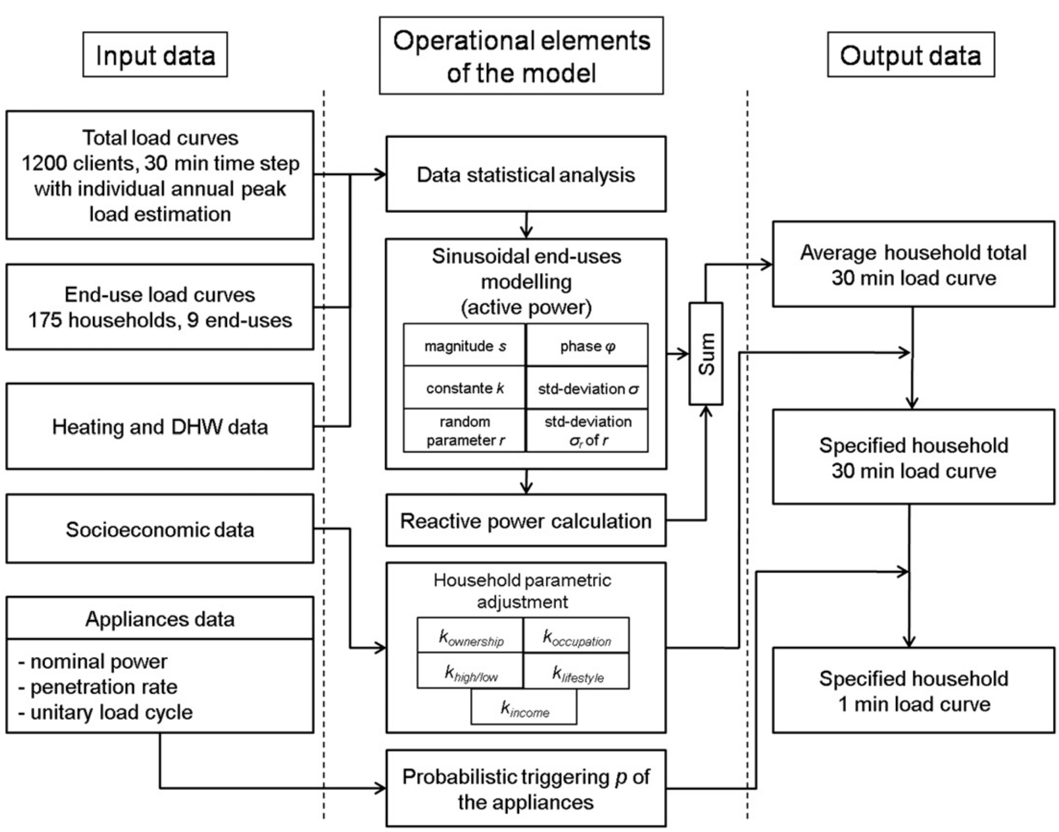

Fig. 6. Bloc diagram of Stokes's model [17].

Because of the lack of 1 min measured load curves which can be used as (calibration) input data and in order to avoid modelling precision discrepancies between appliances, Stokes built up a unique, clear and homogeneous modelling framework that is applied to all end-uses. This way, the level of details of the modelling is the same whatever the domestic device. On top of that, Stokes's model calculates the load factor of each equipment at each time step enabling then to take into account the reactive power demand. According to the author, this part of the power is often neglected in load curve models despite its interest as for instance for load flow analysis purposes.

In the following, the input data for each level, each computing phase with focus on the assumed simplifications, the results of each level and finally the validation of them will be considered.

Input data: In order to calculate the 30 min demand profile for an average household, the 1st level of Stokes's model uses 30 min load curves that have been measured in a sample of 1200 English households. Moreover data at the device level (individual load curves for nine appliances) and knowledge about production and stocking of DHW: this set is differentiated in terms of day-type (three modalities) and tariff (two options). On top of that, information about socio-economic characteristics of the households on the one hand and concerning the dwelling on the other, was available through answers of questionnaires. With regard to the national average, different discrepancies have been identified in the sample by the author.

On top of 30 min demand profile for an average household, the 2nd level of the model, whose aim is the calculation of 30 min demand profile for a specified dwelling, receives information about the penetration rate for each appliance, the occupation of the households (number of occupants according to the dwelling area and presence at home scenarii) and an estimation of its annual maximal power demand value. The type of dwelling, its surface area, its orientation, etc. are other diversity elements that have been considered out of Stokes's work because of the lack of so precise data.

So as to step down at the 1 min time resolution and to provide corresponding load curves for a specified household (load curve that is derived from the 30 min load curve calculated by the 2nd level), the 3rd level gets information concerning the habits of appliance use (e.g. duration and frequency of the cycles), measured unitary load cycles and estimations of maximal power demand per appliance. According to these data, four parameters are defined to characterize the unitary load cycles at the 1 min time resolution: scale of demand, event duration, use frequency and timing.

Modelling details: Stokes's purpose is the modelling of the domestic load curve for average British dwellings. Her model has to be able to provide demand profiles for contemporary situation as future one: so load curves must be adjustable. That is the reason why she decided to assume following statement:

> Variations that affect end-use peak demand and its annual consumption are identical in the time.

Concretely, reduced (normalized) power demand, $P_{r,i}$, for each end-use has been calculated thanks to the Load Research Group[6] (LRG) data set according to Eq. (1)

$$P_{model,i} = \frac{P_{mes,i}}{P_{max_{a,i}}} = P_{r,i} \tag{1}$$

where i is a specified end-use, $P_{model,i}$ is the end-use power data used in the model, $P_{mes,i}$ is the measured 30 min power demand for end-use i and $P_{max_{a,i}}$ is its annual maximal power demand.

[6] See [17] p. 6.

From the LRG data set, Stokes tried to build up a mathematical approximation for 30 min power demand fluctuations on the year. According to her research, the best compromise between accuracy and simplicity is the sinusoidal modelling of the 30 min normalized power demand – $P_{sinusoidal}$ – that is reported in Eq. (2).

$$P_{sinusoidal} = s \cdot \sin\left[\left(2\pi \cdot \frac{N_d}{N_y}\right) - \phi\right] + k + r \tag{2}$$

s represents the sinus function amplitude, ϕ its phase, N_d corresponds to the considered day's number in a year with N_y days. k is a constant and r is a random number generated with an end-use specific Laplace-Gauss density function $[0,\sigma_{sinusoidal}]$.

All parameters derive from the LRG data set. They intrinsically include weather influences: that is the reason why Stokes's model does not make use of "traditional" weather file as input data.

Moreover because of the independence between the Laplace–Gauss density functions, linked end-uses are not considered in Stokes's model.

For certain end-uses (e.g. lighting), minimal and maximal power demand levels have been defined and are applied when Eq. (2) is not relevant or gives negative values. In these cases, 30 min reduced power demand P_r is calculated according to Eq. (3).

$$P_r = \begin{cases} P_{r_{min}} + r_{min} & \text{if } P_r \leq P_{r_{min}} \\ P_{r_{max}} + r_{max} & \text{if } P_r \geq P_{r_{max}} \end{cases} \tag{3}$$

r_{min} (respectively r_{max}) is a random number generated with a $[0,\sigma_{min}]$ (respectively $[0,\sigma_{max}]$) Laplace–Gauss distribution.

Long term consumption trends have been provided by the Market transformation Program [18] for each end-use i. From these, trend estimations of end-use maximal power demand $P_{trend,max,i}$ have been calculated enabling then the scaling up of the normalized demand ($P_{r,i}$) generated by Eqs. (2) and (3). Thus households' group average 30 min (non reduced) power demand – $P_{group,i}$ – is calculated with help of relation (4).

$$P_{group,i} = P_{r,i} \cdot P_{trend,max,i} \tag{4}$$

In her dissertation [17], Stokes adapted the previous modelling approach for various individual end-uses listed in Table 1. Further details about their modelling and the taken assumptions can be directly read in the referenced document.

The results of this level have been validated on measures conducted by the LRG. Comparisons in terms of 30 min aggregated consumption (all end-uses considered) showed the good ability of the model in terms of consumed energy.

Table 1
End-use families and appliances considered in Stokes's model [17].

End-use family	End-uses considered
Domestic cold	Fridge
	Freezer
	Combined fridge/freezer
Heating	Storage heater
Domestic hot water	Immersion heater
Cooking	Hot plate
	Oven
	Kettle
	Micro-wave oven
Wet appliances	Washing-machine
	Tumble dryer
	Combined washing-machine/tumble-dryer
	Dish-washer
Lighting	"Standard" bulb
Miscellaneous	Other appliances

The second level of Stokes's model introduces some influences responsible for diversity in order to produce the 30 min power demand load curve for a specified household.

Income – in relation to the English mean salary – and lifestyle are two elements that influence the use of electricity because household's type of dwelling and corresponding room number are correlated to them: that is why they were integrated into the model. However they are only applied for lighting and miscellaneous appliances on the one hand, they influence the equipment set of the households on the other.

According to the dwelling surface area, that is linked to the number of rooms, the household size (number of members) is calculated. Then household's consumption for each end-use is adjusted according to its size notably with the help of results from Boardman et al. [19] study.

However the presence at home daily profiles and household's occupants' age are two variation sources that are not taken into account in Stokes's model. Nevertheless correlations between lifestyles, penetration rates and daily appliance use were identified in [20] and applied when possible.

In order to calculate 30 min (Half Hourly) load curve for a kind of household (not a precise one) and an end-use i, $P_{HH,spe,i}$, the second level of Stokes's model declines Eq. (5)

$$P_{HH,spe,i} = P_{HH,group,i} \cdot k_{ownership,i} \cdot k_{occupation,i} \tag{5}$$

where $P_{HH,group,i}$ is the calculated half hourly power demand for the end-use i into a group of customers, $k_{ownership,i}$ is a boolean factor indicating the presence (or absence) of the end-use i in the considered household and $k_{occupation,i}$ is a scalar factor that modifies the value of the calculated power demand according to the size of the regarded household.

For some end-uses i, another coefficient ($k_{lifestyle,i}$) multiplies previous equation. It is aimed to take into account the lifestyle (more or less the social status) of the simulated household. For the domestic hot water, $k_{lifestyle}$ is replaced by a coefficient (four modes: very low, low, average and high) whose mode is randomly selected that adjusts the water usage when simulating a sample of households.

The output of the second level of Stokes's model is calculated when adding all the previously determined 30 min load curves for each end-use. However this level does not provide results for a specified household because all dwellings with the same characteristics (household size, lifestyle, domestic equipment set, etc.) will be affected with the same load curves. What introduces variations between them is the third level of the model. It takes the previous calculated power demand profiles as input and considers them as probability distributions to start the end-uses within a day.

In the third level of her model, Stokes tries to explain in detail the diversity of the domestic energy consumption in order to provide the calculation of the 1 min domestic load curve for a specified household. According to Stokes, power demand cannot be modelled without consideration of the chance influence. That is the reason why the end-use launching is determined by comparison between a generated [0; 1] random number and a constructed ratio p calculated as follows:

$$p(\text{event occurring}) = \frac{P_{HH,spe,i}(hh,d)}{P_{HH,app,i}} \tag{6}$$

where p(event occurring) is the probability that an event (the launching of an end-use) occurs, $P_{HH,spe,i}(hh,day)$ is the half hourly power demand value for the end-use i calculated for a specific household at the day d and the half-hour hh and $P_{HH,app,i}$ is the power demand required for a "standard" appliance app that serves the end-use i.

The more the value of the power demand calculated at the second level is high, the more the probability p to start at least one appliance is important. On top of that, the model is able to start several equipments that are related to the same end-use (e.g. lighting) on the one hand, it takes into account the different power demand levels when relevant on the other hand (e.g. hot plates).

Concerning the time start selection of the end-uses, they are chosen with considering individually each half hour. Apart from equipments whose functioning cycle(s) is (are) longer than 30 min, the appliances start times are chosen so that the end-use required energy demand is satisfied into the current half-hour.

The end-use starting frequency and the duration of each cycle are two elements that make the model adaptable. Other assumptions have been made by Stokes for each kind of end-use.

To validate her model, the author makes use of two data sets:

- measures on a bungalow district at the 5 min resolution;
- measures on a sample of 13 households at the 1 min time step

and considers different comparison criteria: energy demand, maximal and mean power demand value (power factor), daily profiles, load distribution density function.

On the first sample, Stokes's model succeeds in estimating the energy demand on the simulation period. However, it seems to be the result of various overestimations and underestimates depending on the considered end-use. In terms of power demand, generated daily profiles are relevant but measured maximal power demand value is always greater than the simulated one. According to the author, it seems to be due to the too low generated diversity.

On the second sample, the same conclusions can be said but on top of that the model gives a general underestimate of the energy consumption and is quite unable to predict the morning and evening peak loads of the domestic customers.

To conclude, Stokes established a very detailed model split into three levels. She adopted an homogeneous modelling framework that makes easier its reuse and modification. Differentiation between end-uses and appliances is carefully taken into consideration. Moreover, the author tried to implement in her model a large set of power demand determinants.

However as we said in the validation paragraph, the generation of diversity reaches its limits because of the use of random coefficients that do not really represent the existing end-use relations. On top of that, the 1 min load curve result for a specified household is partly dependent on the group of measures used for the calculation (because of the load curve "break down" process). Moreover Stokes's model does not explicitly take into account the daily occupation scenarii of the occupants for the end-uses starting algorithm (it is supposed to be integrated in the input data). Finally, the heating power demand and associated energy consumption is only dependent on the dwelling size area: yet the building characteristics, especially the insulation level of the house, plays a determinant role for the thermal appliances.

3.3.2. Paatero and Lund's model

In [21], Paatero and Lund explain the model they have set up. Its aim is to provide 1 h load curve for domestic customers (from few dwellings to a relative large set—1000 clients). Its architecture is represented in Fig. 7.

The authors made use of two main data set as inputs. In fact, there are 1 h power demand measurements that were led on Finnish domestic customers living in flats (respectively during 1 year on 702 households and during 143 days on 1082

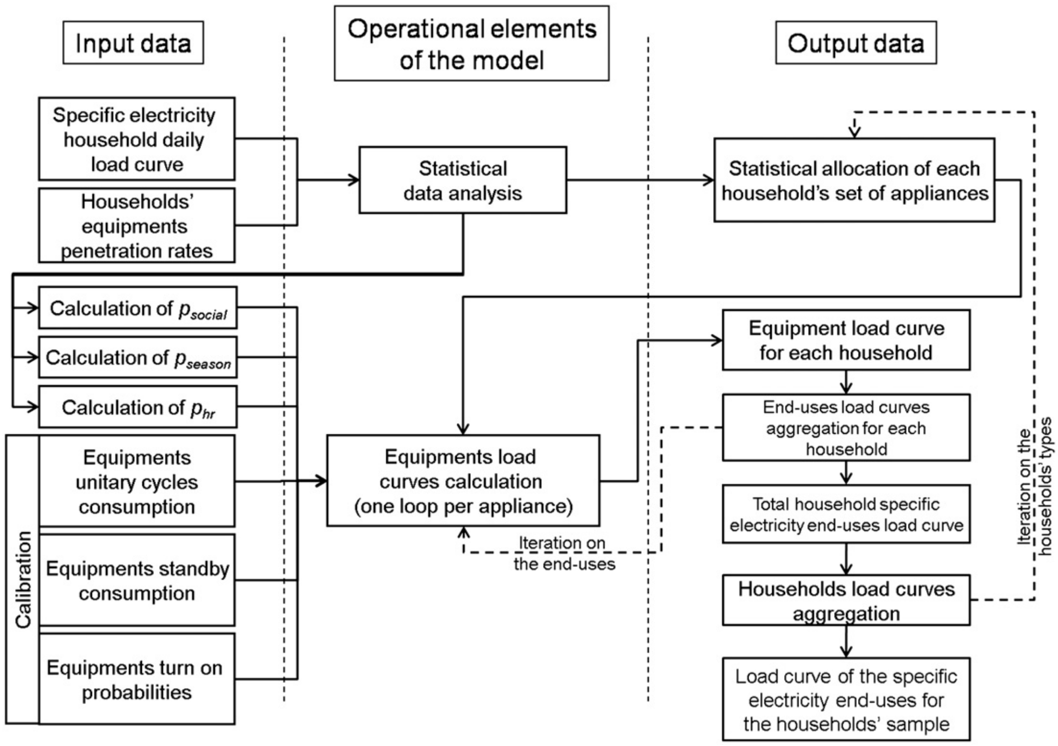

Fig. 7. Bloc diagram of Paatero and Lund's model [21].

dwellings). Because of the absence in the measured apartments of electric heaters, coolers and immersion heaters for domestic hot water supply, these end-uses are not simulated by the model. On top of that, Paatero and Lund used various studies to construct a data base of unitary load cycles and standby power consumption for the simulated appliances. Moreover, they gather national statistics in order to build up the domestic equipment sets.

In order to develop the model, Paatero and Lund studied a series of load curve measures. This way they noticed that power demand fluctuates according to different periods especially the season, the day and the hour. Exogenous influences like outdoor temperature and daylight availability can be theoretically responsible for them. However in this dataset, these influences cannot explain such fluctuations because of the absence of thermal appliances. Domestic habits and social behaviour are responsible for this variability but they did not have been taken into account because it constitutes a too high level of details according to the authors. Moreover Paatero and Lund identify as well as Capasso et al. the deeply interactions between the presence at home of the households' members and conducting domestic activities.

Paatero and Lund constructed a two-level model: the first level defines both the domestic equipments set for each household and the general load fluctuation trend. The second level simulates each appliance in each household with the help of end-use starting probabilities.

To generate diversity, the first level calculates the density function of the domestic daily consumption with help of sample data. The authors have reduced the previous distribution in order to get a dimensionless curve that is centered on the daily mean consumption. Then for each simulated day, a value is selected according to the distribution: it is called p_{social} (social random factor) because it is supposed to capture the social diversity of the demand and it is applied identically for each simulated household. The equipment set in each dwelling is constructed according to the ownership statistics.

The second level of the model provides the hourly load curve for each equipment with considering each household separately. To compute this, two elements are required: the unitary load cycle of each appliance and its starting probability p_{start} calculated according to Eq. (7).

$$p_{start}(i, we, \Delta t, \sigma_{ap}, hr, d) = p_{season}(i, we) \cdot p_{hr}(i, hr, d) \cdot f(i, d) \cdot p_{step}(\Delta t) \cdot p_{social}(\sigma_{ap}) \quad (7)$$

with:

- i is an equipment or a group of equipments,
- hr is the hour of the day,
- d is the day of the week,
- we is the week of the year,
- p_{social} is the social random factor whose standard deviation is σ_{ap} (ap is for apartment),
- p_{season} is the seasonal factor (models the weather influences),
- p_{hr} is the hourly factor (that takes into account the changes in terms of activity levels during the day),
- f is the mean daily starting frequency for each end-use i,
- Δt is the working time step and
- p_{step} is a scaling factor that adjusts the probability values according to Δt.

According to the sign of the comparison between p_{start} and a [0; 1] generated random number, the appliance i is started or not. If the equipment is effectively launched, its load cycle is added to the currently calculated household total load curve. Apart from "cumulative" appliances (such as light bulbs) the calculation of p_{start} is stopped for the equipments during their functioning. As soon as the end of the cycle is reached, the appliance returns then in off-mode and the starting probability can be evaluated again.

Concerning the standby consumption, it is taken into consideration with adding a constant load at each time step.

As a exercise, Paatero and Lund tested their model to calculate the yearly energy consumption of a 10 000 households sample

living in flats. It is not a validation of the load curve reconstitution method because no comparison is carried out on the generated power demand profiles. They only conclude that their model underestimates the mean daily energy consumption and that the distribution of the calculated daily energy use is more spread as the measured data.

Paatero and Lund developed a bottom-up model that is able to provide load curve that are used for instance to quantify the impact of DSM measures. The strength of this method is that it relies on public data and its computational process is relatively simple.

Yet the model is limited in different ways. First of all, because of the used input data, the method is only able to calculate load curve for households living in flats: the data sample is highly non representative of the entire housing stock. Then the model cannot really step back from the past reality because the random influences are constructed on the input data set. On top of that, the model is not capable of evaluating the power demand impact that follows the introduction of new end-uses, appliances or behaviour.

3.4. *Time of use based models*

Time of use data – whose concept was originally developed by Pratt et al. in [22] – generally correspond to daily frequency curves of use for each end-use/domestic activity. In order to construct this kind of information two main ways are available:

- a monitoring campaign is realized in a sample of households and during the study time each household's member has to write down in diaries the conducted domestic activities at the time step resolution that is chosen for the campaign,
- the other way is to focus the study on different general domestic activities (breakfast, lunch and dinner time, get up and bedtime time, daily transport duration, etc.) and to reconstitute an incomplete diary with mean times of each activity with a density function around these moments.

Then the compilation of the results enables one to obtain frequency curves for the studied activities by comparing for each time step the number of households where a specified activity is being conducted with the total number of studied households. The segmentation of the results can be done for each end-use with the same methodology if the study has been conducted on the domestic equipment basis. Moreover it is possible to get curves for different types of day (it is often divided between weekday and weekend day). This concept enables the modelling of domestic activities and it provides realistic sequences of electric equipments use in a sample of households.

3.4.1. *Walker and Pokoski's model*

Walker and Pokoski [23] are the first authors which use the concept of time of use with the aim of constructing a load curve model. More precisely they are the first who take into account human behaviour to reconstruct load curves for a specified household or a set of different dwellings. The model was developed so as to help the planning of new power plants and it gives total load curves at 15 min time step.

The basis of the human behaviour modelling is the use of two kinds of probability functions respectively called availability and proclivity which will be then generalized in the model of Capasso et al. (cf. Section 3.4.2). The first one gives the household's occupants probability to be at home and so "available" to use an electric domestic appliance. Concretely it is implemented in the model with 96×1 daily vectors (the time resolution is 15 min – $96 \times 15 = 1440$ min $= 24$ h) containing 0 and 1 indicating respectively on the one hand the absence or the asleep state of a person and, on the other hand, the presence at home of a specified household member in an awake state. Theoretically in order to represent the exact reality, the input data required for this function is one occupation diary per studied person. Consequently these data-gathering can be very expensive. That is the reason why Walker and Pokoski only make use of one presence scenario and they improve it with variations sources thanks to different density functions implemented at the start times of the main activities. In this way they get various "mathematically constructed" occupation daily scenarii. Yet the authors had to take into account the different ways people live: typically the time to go to work and to come back from work generally in the evening. Delay probabilities were defined in accordance with the estimated proportion of each "way of life" in the simulated area. All things considered, the availability function is constructed with help of 13 sub-functions, each one gives a unitary kind of information. Moreover Walker and Pokoski take into consideration the absence from home because of non professional reasons (hobbies, shopping, etc.): they model this influence with the help of P_{away}, a probability function which makes dependent on it the availability function. P_{away} is compared with a random number generated with a [0; 1] uniform density function. Two ways are then adopted in order to calculate the number of occupants at home for each time step according to whether P_{away} is bigger or smaller than the generated random number.

The availability function gives not enough information in order to reconstruct the load curve of a set of households. That is the reason why the authors make use of various proclivity functions which model domestic habits and more precisely time periods when they are likely to be conducted.[7] The proclivity for a certain activity is equivalent to the tendency to do it during a day. These preferential time periods come from standards of living, conventional ways of life or even people habits. In fact there are two kinds of proclivity functions:

1. the first one indicates the likelihood for the use of a specific individual electric appliance;
2. the second type considers a domestic activity which may require the use of various equipments.

In order to construct the first proclivity function (the so called basic proclivity function), Walker and Pokoski make use of different results coming from various surveys whose aim was the construction of a daily diary for a selection of domestic appliances so as to know the periods when they are likely to be used and the weekly frequency of turn on events.

The second type of proclivity functions represents more general activities such as the daily mealtimes. Potentially this activity involves the use of a few domestic equipments such as the fridge, the range and/or the water heater because of the very possible draw of water for this activity. With help of results from various studies, Walker and Pokoski define density probability functions for each mealtime of the day. This way each period in the day is affected with a probability that meal can be taken during this time period. Such probabilities can be defined for other activities.

With the help of the availability and the proclivity functions, the authors have the knowledge concerning the moments when the electric appliances are turned on during the simulation time. To get the corresponding load curve for each end-use they have to "stick" on the identified on/off events, unitary load curve patterns that are specific for each appliance. In the case of the appliance

[7] Without excluding their respective probability at any other time in a day.

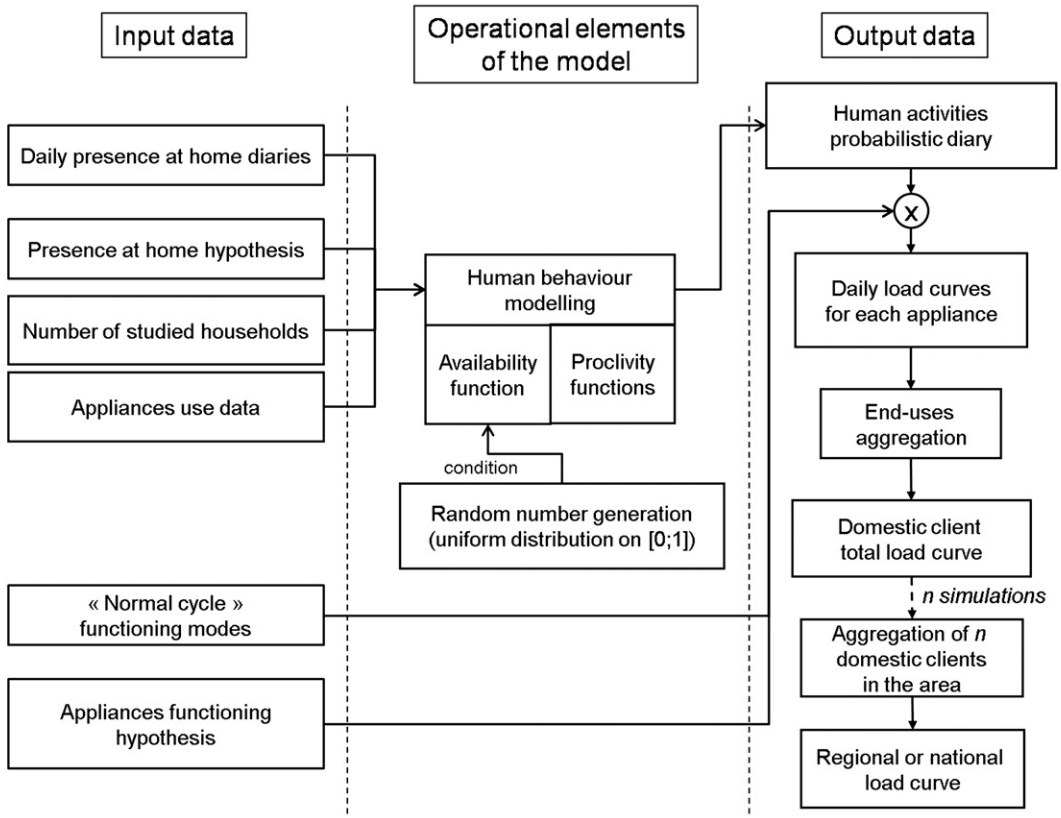

Fig. 8. Bloc diagram of Walker and Pokoski's model [23].

which run without the need of a human intervention (for instance, they are turned on or off according to the information which is provided by sensors), Walker and Pokoski use what they call "normal-cycle" functions. It is notably the case of the fridge which runs all the time with a cycling on/off alternation.

The architecture of the model is presented in Fig. 8.

Fig. 8 shows the chosen aggregation method. In fact, the simulation tool provides individual end-use load curves (one curve per electric appliance). These raw results are then aggregated according to two steps:

1. first a summation is done at the household level achieving then the total load curve for a specified dwelling;
2. secondly the total load curves are aggregated in order to get the global load curve of the simulated area.

This modular architecture enables one to consider the influence of the power demand of an individual appliance with regard to the total demand of the household. Another advantage of this technique is the possibility to add a new appliance in the model without reconstructing its whole structure and with conserving the calculation method. Moreover the simulation provides the load curve of an area which is not calculated as an individual household's mean load curve multiplied by the number of simulated dwellings. Thus real behaviour with potentially huge differences between them can be simulated. Furthermore it gives the opportunity to simulate a lot of dwellings with different sets of domestic equipments.

In [23] only the water heater is presented in detail but the entire model is described in [24] and at the date of the publication the model did not contain thermal load appliance (such as heater). However Walker and Pokoski did not consider this feature much more complicated than the water heater because, according to the authors, it only requires another function which takes into account, on top of the availability and proclivity information, the in- and out- heat flows affecting the dwelling and economic considerations concerning the occupants.

To validate their model the authors carried out two simulations. The first one had the aim to obtain the daily load curve for two single-family homes. The second test concerned two groups of residences. Simulation results were compared with data from a load curve measurement campaign. The chosen criteria for the comparison was the Normalized Variation Factor (*NVF*) defined as follows:

$$NVF = \frac{\frac{1}{n}\cdot\sum_{t=1}^{n}(P_{est}(t)-P_{mes}(t))^2}{\overline{P_{mes}}^2} = \frac{\frac{1}{n}\cdot\sum_{t=1}^{n}(P_{est}(t)-P_{mes}(t))^2}{\left(\frac{1}{n}\cdot\sum_{t=1}^{n}P_{mes}(t)\right)^2} \qquad (8)$$

with $P_{est}(t)$ the estimated power demand at time t, $P_{mes}(t)$ the measured power demand at the same time and n the number of simulation time steps. Conceptually the *NVF* corresponds to a "pseudo-variance" of the estimated power demand calculated with reference to the measured load curve that is normalized by the square of the mean measured power demand value. So *NVF* represents the dispersion of the estimated power values compared to the measured ones. *NVF* is reused by Capasso et al. [25] and Widén et al. [26].

With this indicator, the authors tried to know if their results are included in the fluctuation range existing between two daily measured load curves. In fact, it is possible to calculate the *NVF* for the same household (or group of households) between different days or for the same day and between different households. They got good *NVF* values (i. e. small figures) confirming the fact that the simulated load curves fit the measured ones.

3.4.2. Capasso et al.'s model

Capasso et al. present in [25] the model they developed which is called ARGOS. Its aim is to reconstruct the load curve for a

specified household up to a set of dwellings, in a defined area, in order to quantify the impacts of DSM measures. These are taken namely so as to provide a solution for one of the major problems affecting the Italian electricity network: the winter peak load occurring during worked days. Another purpose of this methodology is to be a tool for optimizing the production of the power plants or even to "drive" the planning of new energy supply sites. The main characteristic of this approach is the fact that it takes into account the major interactions between the electricity energy demand and the behavioural factors. The results are load curves with a 15 min time resolution.

From results of various surveys, the authors constructed some probability functions. They notably make use of the Walker and Pokoski's availability and proclivity functions enabling then to obtain mean profiles for the basic proclivity function.

ARGOS simulates the load curve of a residential customer. This is built up with a set of domestic appliances and a specified number of occupants. According to Capasso et al. the real issue for calculating domestic load curves is the modelling of the interactions between the set of equipments and the household's members.

So as to set a realistic modelling frame, rules and constraints are programmed in ARGOS under a probabilistic form: there are behavioural and engineering functions.

On the one hand, the first ones define the appliances set for each household according to its characteristics. On the other hand, they establish the specified household corresponding time structure for the use of the equipments. That is to say that the domestic activities, which are grouped together in four main families (cooking, housework, leisure and personal hygiene), are not randomly conducted by the occupants through a day, the starting of the equipments too. On the contrary, they are both spread in the simulated day thanks to time of use density functions. These are calibrated so that simulations lead to appliances daily consumption that are included within a confidence interval around values coming from measurements. Simultaneously each household member is characterized with a presence at home scenario and a specific proclivity for each domestic activity.

The engineering functions give various information: first they precisely characterize the functioning of each domestic equipment according to its properties, secondly they set each household subscribed maximal electric power and finally they set the technological penetration in the simulated population.

The previous described data and probability functions (behavioural and engineering ones) are stored in a file which actually contains all required inputs of the model.

From the parameters that describe the scenario, a Monte Carlo extraction is carried out to choose the simulated type of household. The corresponding total load curve is calculated in ARGOS by addition of each end-use specific load curve.

The total load curve for a complete area is simply calculated by addition of the individual consumer's load curves. The architecture of ARGOS is shown in Fig. 9.

As model validation task, Capasso et al. tried to reconstruct the aggregated load curve of 180 apartments which are representative of the Italian dwellings located in the main cities' suburbs. Among them, only 95 households have been kept as comparison references because they answered a questionnaire whose results built up the ARGOS input data file.

As we previously said, this model was established especially to predict the residential load curve during peak load days. That is the reason why, the authors focused the comparison results on restricted time periods. For these critical hours, modelled and measured load curves are very similar. For other infra-day periods, comparisons are less favourable.

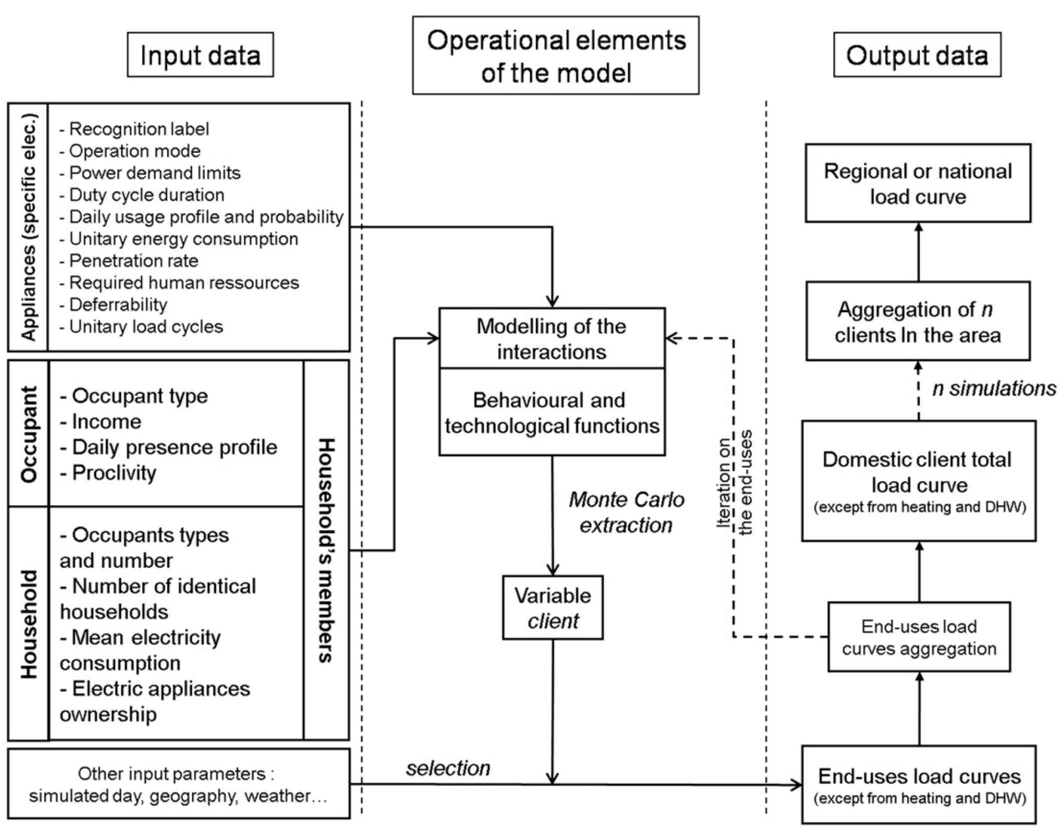

Fig. 9. Bloc diagram of Capasso et al.'s model [25].

In a second step, the comparison period was extended to a complete simulated day. For this task, Capasso et al. estimated and compared the *NVF* between measured and modelled load curves on the one hand and between two consecutive daily measured load curves on the other. Results satisfied the confidence interval criterion indicating the good approximation ability of the model.

ARGOS constitutes a noticeable improvement of the Walker and Pokoski's model and in the same time a comparison reference for the models developed after it, especially for the human behaviour modelling. Finally, this is notably well reproduced because of the use of real elements instead of standardized occupation profiles as in Yao and Steemers's model. Another advantage of ARGOS is its ability to provide the load curve results under various aggregation levels enabling then the calculation at different scales of load curve specific coefficients. Moreover, new appliances can be implemented in the model, rules and constraints are changed and adapted by the user.

Yet, these possibilities require a lot of input data that are difficult to get at a large geographic scale (i. e. the simulation of the national domestic load curve seems to be illusory). On top of that, the needed information for the elaboration of the behavioural functions have been systematically adapted into Laplace–Gauss distribution. This can lead to non optimal adjustments in all cases. Some significant distinctions in setting the parameters of the simulation have not been taken into account: worked day/not worked day, winter/summer, etc. Nothing about building diversity (for instance thermal characteristics) has been implemented in ARGOS because of the relative insignificance of electric heating in Italy. Finally, the influence of the electricity tariffs is not supported by this model.

After the first model implementation in FORTRAN, research has been resumed and continued by Prudenzi, Falvo and Silvestri. This work leads to a new software called DELOS (see [27,28]). However no significant evolutions have been added in this model compared with the initial one (ARGOS): in particular the concepts remain the same.

3.4.3. Armstrong et al.'s model

In the framework of Annex 42 of IEA (International Energy Agency) "The Simulation of Building-Integrated Fuel Cell and Other Cogeneration Systems (COGEN-SIM)", Armstrong et al. [29] established a model which reconstructs the load curve of domestic specific electricity appliances with a 5 min time resolution. The aim of the modelling task is to obtain various typical consumption profiles for the selected appliances so as to determine the way micro combined heat and power (μ-CHP) can be integrated in Canadian dwellings and how they can provide the required power.

In this frame, three target households have been simulated. They differ in terms of dwelling surface area and intensity of energy consumption.

Armstrong et al. make use of information and notably:

- estimated target household annual energy consumption for each selected appliance[8] thanks to three sets of use factors[9] that compare actual with national average appliance energy consumption,
- domestic equipment set with their characteristics (inclusive penetration rates[10]),
- and occupants' use profiles.

This wide set of information was established thanks to surveys, statistical and appliances manufacturers data; it is representative of the situation of the Canadian domestic appliances stock in 2003.

On top of that, information about unitary load cycles, cycles duration, estimated month equipment use and appliances typical nominal power have been used by the authors.

Moreover time of use data have been implemented in the model. Because of the lack of these kind of information, Armstrong et al. reused the TOU profiles defined by Pratt et al. [22] for some appliances (range, dish-washer, washing machine) without any modification. For other devices, they performed some adaptations on the available profiles.

The load curve construction methodology, which is schematically illustrated in Fig. 10, relies on simple principles and assumptions regarding on the one hand the timing and on the other hand the magnitude of the power demand.

The management of the appliances starting is performed with the help of the TOU curves and an appliance specific chance factor c that provides the estimation of the hourly probability p of a start event according to the equation:

$$p = \frac{f}{c} \tag{9}$$

where f is the hourly fraction of the daily use (hourly TOU value). For each household's appliance, c value was set by iteration so as to meet the target consumption via the annual cycles number.

With regard to the magnitude of the load curve construction and despite the individual simulation of each device, less modelling methods have been developed than the number of different appliances. So it means that a same method was applied to several devices whose functioning showed similarities.

In fact, simplified modelling approaches have been chosen by the authors:

- assignment of a constant power demand during the functioning of washing and cooking appliances;
- the power demand of domestic cold appliances is directly constructed from measures that are adapted by the authors to match the consumption targets;
- the load curve of lighting and other appliances is constructed from the TOU curves, a duration use that is randomly selected between chosen lower and upper bounds and nominal power values;
- a 65 W base load represents the stand-by power demand of the domestic equipments in the household.

Then Armstrong et al. proceed with an aggregation step to get the daily load curve for a specified household: the eight previous calculated loads (one per appliance) are simply added up. The yearly load curve for each dwelling type is obtained when performing multiple simulations.

In order to evaluate the goodness of fit of their model, the authors carried out comparisons between simulation results and load curve measurements. These have been collected by Hydro Quebec in the 1990's during a campaign focused on electric heated detached houses. With this campaign total, heating and DWH loads have been simultaneously measured at a 15 min time resolution. By difference, specific electricity load curves were obtained. Four houses from this campaign have been selected to proceed the evaluation task.

First, the visual comparison showed the good ability of the model to be near the reality in terms of peak loads, mean loads and annual energy consumptions.

[8] Fridge, freezer, dish-washer, washing machine, tumble dryer, range, lighting and other appliances.

[9] Non validated coefficients.

[10] Because of the choice of the target dwellings, the authors adapted the national penetration rates. Concretely they systematically assigned for each household some selected appliances (fridge, freezer, dish-washer, washing machine, range and tumble-dryer) and they applied target household specific hypothesis.

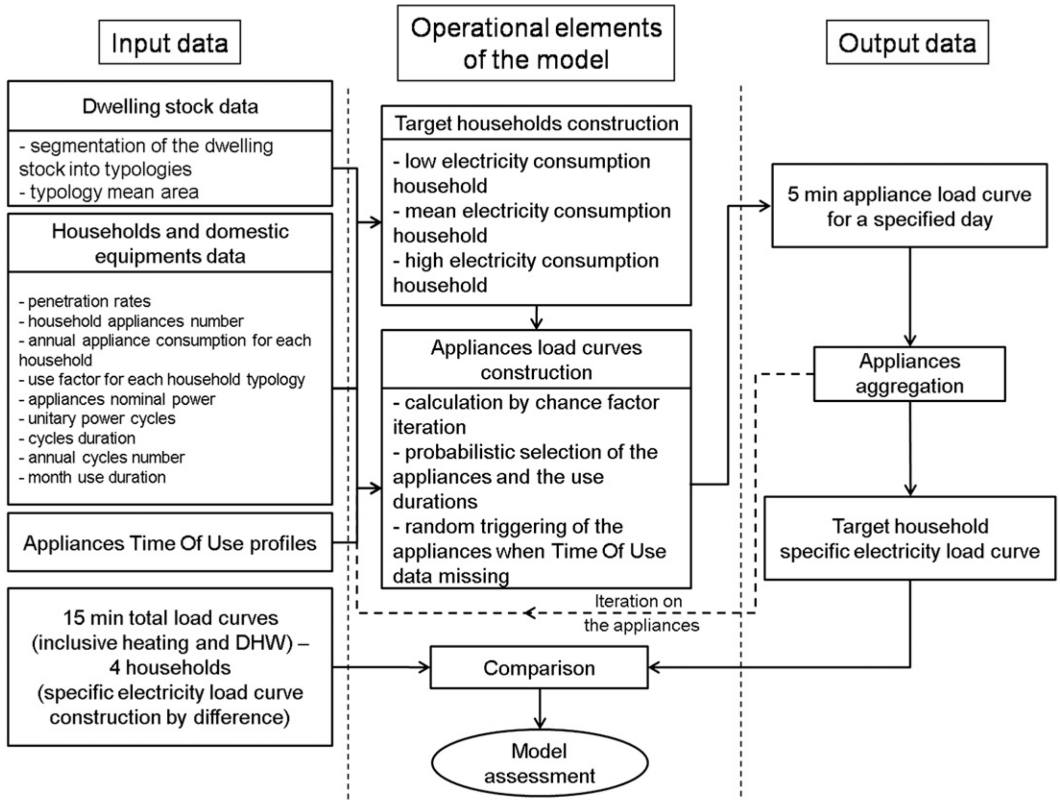

Fig. 10. Bloc diagram of Armstrong et al.'s model [29].

Secondly, Armstrong et al. notice that the model produces less repetitive results than what is seen in the measurements. For the authors it does not constitute a weakness of their model since the generated loads will be used as inputs for the simulation of μ-CHP: variable demand profiles lead to stress on the CHP that are more difficult to comply with.

Thirdly a statistical comparison (study of the repartition of the values in 100 W ranges) has been proceeded leading to two main observations:

- the selected power level for the modelling of stand-by modes (65 W) is not optimal;
- the second observation is more trivial: in measures, two 100 W-ranges of power demand are empty what is not the case of simulated results. This can be explained by the domestic appliances sets in the selected households.

This load curve reconstitution tool shows a series of advantages: first its relative simplicity, secondly the reasonable required amount of input data compared with the other models and thirdly its ability to generate various specific electricity demand profiles. Yet some weaknesses can be found: the used TOU curves probably have few validity because they are not recent (1989): domestic habits can evolve significantly. Moreover, apart from the used load curves for refrigerators and dishwashers that come from measures, the other unitary load cycles are built up when assuming a constant power demand during the functioning what is a real simplification of the reality. Finally the model does not make the difference between the types of the days (weekday, weekend days for instance) and the influence of the weather only concerns the lighting and it is very simplified in this case.

3.4.4. *Widén et al.'s model*

Widén et al. expose in [26] the load curve generation model they built up. This TOU data based model makes use of simplified end-use to power demand conversion schemes, natural daylight density function and water consumption; moreover it defines and simulates "mean"[11] domestic equipments.

The main purpose of this model is to generate electric load curves for domestic appliances that will then serve as inputs of other simulation tools. Among them are modelling programs of small scale decentralized electricity generation systems or domestic water production equipments based on solar energy. Another purpose of this simulation tool consists of studying the modifications on the domestic load curve in a prospective point of view when considering the changes in terms of behaviour and energy efficiency of the appliances.

In the authors' opinion, a load curve generation model can be classified according to two criteria: its spatial and temporal resolution.

The spatial resolution corresponds to the smallest simulation level where a tool is able to provide a curve of need (electricity, heating, water, etc.): from a unitary domestic equipment to a household type to the national residential field. The temporal resolution of a model is linked with the time step results are returned: from seconds to hour.

In terms of input data, the main requirements of this model are time of use information with a 5 min time resolution that have been collected during a series of campaigns. Concretely, it is constituted by empirical presence at home scenarii and domestic activity sequences for a weekday and a weekend day. During them, each occupant of the selected households had to

[11] In terms of performance.

write down his activities and the corresponding start and stop times of them. That notably includes the instants when getting up and to go to the bed and when moving out and to home. Thus the model provides a load curve for each household's member and can construct load curves for a mean domestic customer.

On top of time of use information, end-use load curves measurements and domestic water profiles have been used for the elaboration of this model.

In the whole, five surveys have been used as input data sources, comparison elements data bases and validation references.

The original characteristic of Widén et al.'s model, whose architecture is described in Fig. 11, is the use of end-use to power demand conversion schemes. This leads to a simple modelling way rather than a very precise one complying with the authors' wish that is a satisfactory load curve representation at a 1 h resolution.

Concretely, for each domestic activity that implies an electricity and/or a water consumption the authors assign a standard end-use pattern; each of them is described by a series of parameters. These were set so that a realistic average consumption is got when they are applied to the simulated households. Nominal power and use duration were estimated, thanks to a campaign of tests. Activities whose electricity and/or water needs were insignificant have been neglected. This modelling approach constitutes an essential feature of Widén et al.'s model.

Thus, five possible schemes have been built up:

1. either power demand is disconnected from the activity. That is the case of cold appliances whose modelling is a constant power demand in functioning mode;
2. or power demand is constant during the activity. This scheme is applied to a lot of domestic activities from cooking to ironing and to TV watching. Thus it constitutes a strong assumption in the sense that it is applied to very different appliances;
3. or power demand is constant after the activity. Dishwasher, washing-machine and tumble-dryer are concerned by this scheme. In fact, the corresponding domestic activity is the filling up of the washing appliance. Although power demand effectively is required immediately after the end of the domestic activity, the authors admit that they widely simplify the reality;
4. or power demand is constant during the activity with addition of a temporal constraint. This scheme is applied to the majority of activities that imply domestic hot water especially when drawings-off occur in the first part of the task. The constraint restrains the reuse of already drawn hot water for the following activities;
5. or finally the domestic activity requires a fluctuating power demand. The modelling of lighting follows this assumption. More precisely, the power demand fluctuates according to the available daylight: if somebody is at home in an aware state (i. e. not sleeping) the maximum power demand level P_{max} is applied when the daylight availability L is low (under a L_{min} level) and the other way around (P_{min} when $L > L_{max}$).

Because of the lack of information concerning the use of DHW, the authors had to make use of empirical rules.

Widén et al.'s model was developed in MATLAB. Load curve time resolution can be selected by the program user (from 5 min to 1 h). Distinction between detached house and flat on the one hand and between weekday and weekend day on the other is made by the simulation tool.

As validation, the authors simulate the power demand requirements of the households described in the 1996's statistical survey (that contains among other things time of use data and equipments characteristics) and compare them with the results coming

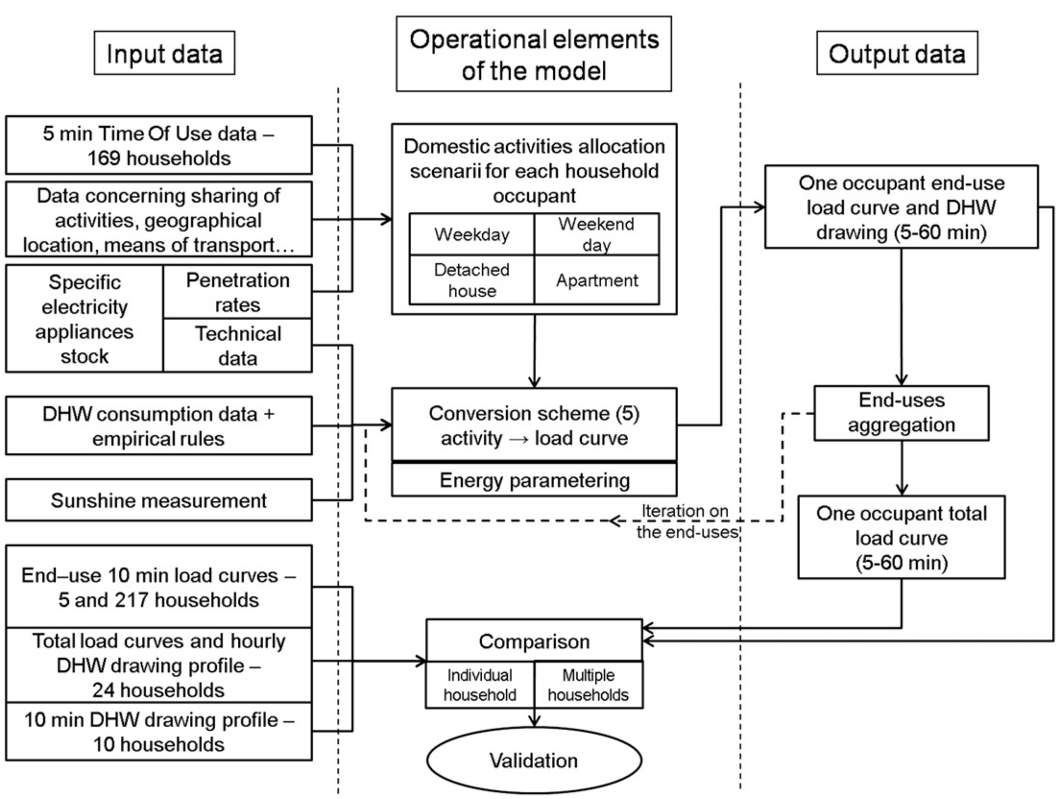

Fig. 11. Bloc diagram of Widén et al.'s model [26].

from the latest (2006) available load curve measuring campaign. Thus, two assumptions are conceded: domestic appliances and TOU data have not changed significantly between 1996 and 2007 enabling the possible use of the input dataset.

To some extent, the results (individual households' total load curves, i. e. all simulated end-uses aggregated) are in accordance with the comparison references notably in terms of load curve shape and load peak prediction (high consumption days and households).

Yet, Widén et al. notice that the relevance of the results becomes weaker when considering the end-uses separately. For instance, the power demand modelling for end-uses that are simulated according to the second conversion scheme is more satisfactory than these when power requirement and activities are disconnected.

Moreover, the authors carried out other simulations in order to make comparisons at an aggregated scale especially on a households sample that represents the Swedish population. The model shows a good ability to differentiate the average power demand shape that characterizes a detached house from an apartment on the one hand, a weekday from a weekend day on the other. To go further in the comparison, the authors calculated the *NVF* for some end-uses: this shows similarities between measures and simulations. Yet when observing more precisely the outputs of the simulation tool, some discrepancies can be shown as for example an undervaluation of the power demand for a detached house during the night. Widén et al. suggest that this is due to the miscellaneous end-uses that are not considered by the model. Other divergences can be seen as for instance temporal move of the modelled peak load for some end-uses compared with measurements.

From TOU data and information about the stock of domestic appliances, the authors built up a simulation tool that reconstructs load curves for different households' and days' typologies. With the help of a restricted number of domestic activity to power demand conversion schemes, Widén et al. get satisfactory results when considering the load curves at aggregated scales (wide simulated sample, 1 h time resolution).

However, the tool is directly modelled on the available time of use data, that is to say that it represents the 1996's situation (non scalable modelling). On top of that, these data have been collected in diaries that were filled in by the selected households' occupants. The use of the collected data needs a good quality of them what is not ensured as underlined by the authors. Moreover, there is no modelling of electricity consumption diversity because it is embodied in the input data. As a consequence, the integration of a new end-use seems to be difficult because it implies the implementation of the corresponding time of use scenario in the available diaries. The model corresponds to the Swedish housing stock where electric heating appears as an exception. That is the reason why this end-use (and the thermal issue in general) is not considered in the model.

At the end of [26], Widén et al. list the possible improvements of their model: they notably announce the use of a Markov-chain and of density functions to generate diversity in terms of human behaviour on the one hand, its changes in time on the other. These evolutions have been implemented later in Widén and Wäckelgård's model.

3.4.5. Widén and Wäckelgård's model

In [30], Widén and Wäckelgård expose the model they developed: this is an high time and spatial resolution tool that generates domestic activities scenarii. These are then converted into electric load curve.

The main improvement of this model compared with Widén et al.'s is the use of a non homogeneous Markov-chain that generates diverse domestic activities sequences with high resolution levels (1 min time steps, modelling of each household's member). Only the activities that imply electric power demand are taken into account by the model: heating and domestic hot water supply[12] are notably excluded.

Load curve synthesis follows the same two-step process as in Widén et al.'s model:

1. domestic activity patterns are allocated to each dwelling's occupant;
2. activities are converted into power demand thanks to conversion schemes.

The functional architecture of the model is schematically represented in Fig. 12.

As expected, input data of this model is the same as the previous model's: time of use for domestic activities coming from statistical surveys and weather data. From these sources of information, a Markov-chain (firstly applied to the lighting and fully detailed in [31]) has been built up: this is the main feature of Widén and Wäckelgård's modelling approach. The model assumes that at any simulated time t, each occupant of a household must be in one of the three following availability states:

- absent: the person is not at home;
- present and inactive: the occupant is at home and sleeps;
- present and active: the dwelling's member is at home and can carry out each kind of domestic activity.

Nine domestic activities/end-uses[13] are dependent on these availability states especially the "present and active" that makes them possible: in the Markov-chain, they are represented by a code (number). Domestic cold and lighting are independent of last availability state and are not driven by the Markov-chain.

Starting with the carrying out of the domestic activity a_1 at time t, the stochastic process calculates the transition probability to change to activity a_2 ($a_1 = a_2$ or $a_1 \neq a_2$) at $t+1$ with help of the input data. Transition probabilities have been calculated at a 1 h time resolution. Even if load curves can be computed at a better resolution, activities' transition probabilities stay constant over one simulated hour. However the probabilities are not fixed along the day (non homogeneous Markov-chain), so the daily fluctuations of the activities are taken into account by the process. At each time step, these calculated figures are compared with a random number generated by a $[0; 1]$ uniform density function. According to the sign of the difference, activities are launched or not.

The detailed calculation process is described in [30]. For few cases, the authors adapted it to ensure its coherence (especially for night periods).

As in Widén et al.'s model, domestic activity to load curve conversion schemes have been built up with help of measured load curves. Moreover these have been refined compared with those in [26] especially in three points:

1. appliances' power demand can occur before, during, just after the corresponding domestic activity or even totally disconnected from it;

[12] Very little electricity demand is dedicated to these end-uses in the Swedish housing stock.

[13] Away, sleeping, cooking, dish-washing, washing, TV, computer, audio appliances and other devices.

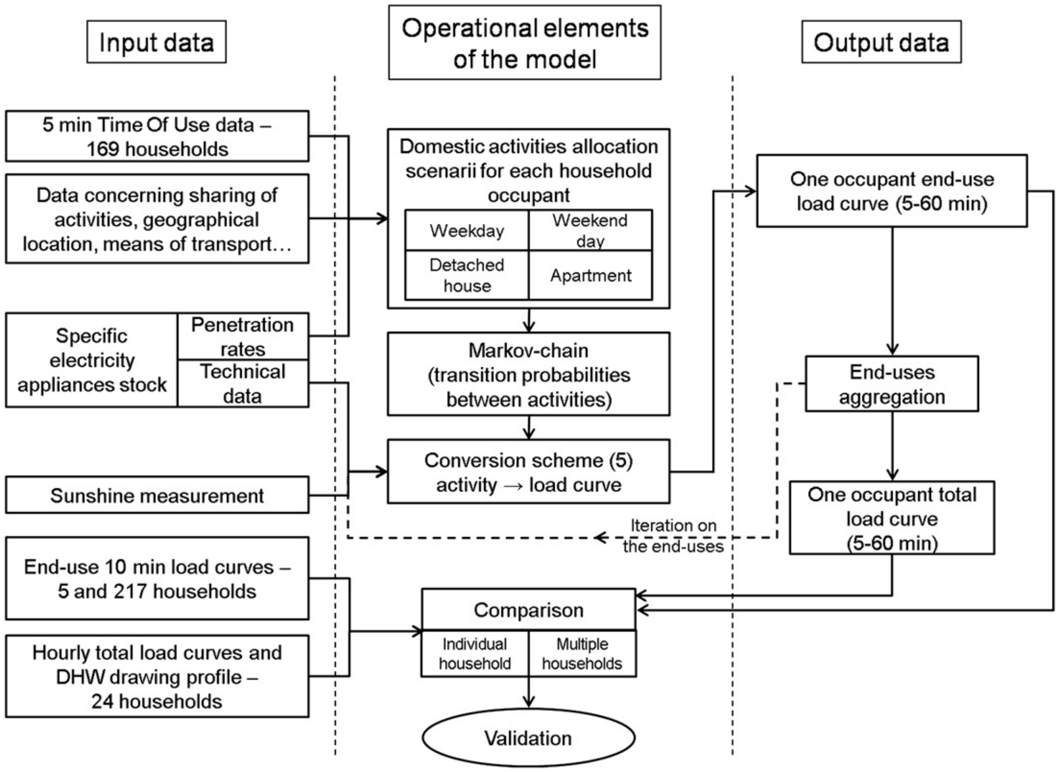

Fig. 12. Bloc diagram of Widén and Wäckelgård's model [30].

2. unitary power demand pattern and stand-by power level are characteristic of each appliance;
3. appliance sharing between household's occupants is taken into consideration.

Concerning this last point, the authors underline that this kind of data are not recorded in the time of use diaries. Thus a supplementary assumption is made by Widén and Wäckelgård: a few appliances are totally shared by all dwelling's members (e.g. the fridge) whereas some other are systematically used by a single occupant. According to the device status, the related domestic activity can be carried out by several people at the same time (leading to a single power demand cycle) or not (the activity can only be conducted by a single person and it systematically leads to a power demand pattern).

In [30], more details are given about the modelling of each activity related appliances. In fact, assumptions should have be done in order to adapt the modelling method to each domestic device (respectively each appliance related to the same domestic activity).

So as to validate their model, Widén and Wäckelgård proceeded with two kinds of modelling tasks and comparisons taken the Sweden Energy Agency's data as references: first they tested the model on a small scale housing stock (14 dwellings) in order to evaluate the ability of the model to generate diversity. Then they compared the generated load curves at a more aggregated scale (two hundreds simulations for a similar dwelling type during a week – five weekdays and two weekend days, two dwelling types considered detached house/flat) so as to know if the model provides a good approximation of the energy consumption with regard to the statistical national energy consumption data.

To compare simulated and measured load curves, the authors chose the two following criteria:

- the load factor $F_{n,Pmax}$ related to the maximal power demand for a set of n clients during an interval Δt:

$$F_{n,Pmax}(\Delta t) = \frac{P_{mes,n}(\Delta t)}{P_{max,n}(\Delta t)} \tag{10}$$

  with $P_{mes,n}$ and $P_{max,n}$ respectively the mean and maximal power demand required by the n consumers over the time period Δt
- the diversity factor $K_{f,n}$ related to n electricity users and the time slot Δt:

$$K_{f,n}(\Delta t) = \frac{\sum_{j=1}^{n} P_{max,j}(\Delta t)}{P_{max,n}(\Delta t)} \tag{11}$$

  where $P_{max,j}$ is the maximal individual power demand value for the client j and $P_{max,n}$ is the maximum demand of the n consumers considered in the whole.

Both equations give a summarized analysis when considering different power demand profiles and thus explain their frequent use in such a study.

In the whole, comparisons provide the same kind of conclusions that have been made for Widén et al.'s model: the simulation tool gives satisfactory estimations of domestic load curves, generates sufficient differences in terms of timing and magnitude of the power demand between weekdays and weekend days on the one hand, between house and flat on the other hand.

However some improvements can be carried out such as a better modelling of some end-uses, a refinement in terms of domestic activities and a more suitable distribution of the domestic equipments according to the dwellings' properties. Carrying out these evolutions necessarily requires more detailed

input data. These come from surveys and their precision directly depends on the attention of the selected people sample. Moreover, the model is only relevant for short term forecasting since time of use data always represents the past situation. This is notably what causes the little ability of the model to simulate the Information and Communication Technologies (ICT) load curve (the computer is the best example). Thus to maintain a satisfactory precision of the model, updated time of use data have to feed the simulation tool imposing regular to continuous surveys. Although heating is not considered in this model, the authors underline that its integration is feasible. Yet, without apparent help of a building simulation tool, we can wonder about the precision of this end-use modelling.

3.4.6. Richardson et al.'s model

In order to quantify the impact of "low carbon measures", such as demand response and CHP, on a local electricity distribution network, Richardson et al. developed a model presented in [32].

The authors adopted a "deep" bottom-up approach since the simulated elements are the specified household's domestic equipments and the households' members whose individual behaviour modelling is based on activity diaries built up from surveys. Thus Richardson et al. are able to reconstruct the 1 min electric load curve corresponding to a few number of dwellings located in the same area. According to the authors, this simulation time resolution has been considered as the best compromise between the amount of produced results and the required precision level at a small spatial scale.

The structure of the simulation tool is schematically drawn in Fig. 13.

As Fig. 13 underlines, Richardson et al. made use of the results of a time of use survey in order to get availability scenarii (presence at home and awake state). According to the authors, the occupant's state "at home and active" is the most interesting because in this case electric devices can be run. In the model, this kind of information is coded by a binary variable which equals 1 when an occupant is at home and active, 0 otherwise. An aggregated availability profile is obtained when adding each occupant's availability variable.

Yet the active occupation only corresponds to the necessary condition to use an equipment, the next step to construct a load curve is to know the kind of device that is run, the use duration and the start times. That is the reason why Richardson et al. have made use of daily activity profiles (probability density over the day at the diaries' time scale) elaborated from the TOU survey for seven different domestic activities. Here we recognize the same input material as in Widén and Wäckelgård's method [30]. However these elements differ from the Swedish model because they are "static": in Richardson et al.'s model, daily activity profiles are only functions of the day-type (weekday/weekend day) and the number of occupants in the simulated household (from 1 to 5). Using such kind of data enables a realistic human behaviour modelling on condition that first diaries have been written down carefully and secondly the people sample is large enough to "smooth" domestic habits.

So as to provide a satisfactory device modelling, Richardson et al. used statistical information (penetration rates, devices' and households' annual consumption) and some measured power demand patterns – all input data are available in [33]. When this last type of information was unavailable for the appliances, constant power demand has been assumed. They sometimes had to adjust them in order to reach the average East Midlands's household that constitutes the target annual domestic consumption.

Domestic activities can imply the need of electricity without forcing it. That is the reason why Richardson et al. had to make connections between activities and appliances: according to the authors' classification of the considered domestic activities (watching TV, cooking, laundry, washing/clothing, ironing, cleaning, other activities), some links are obvious because one activity

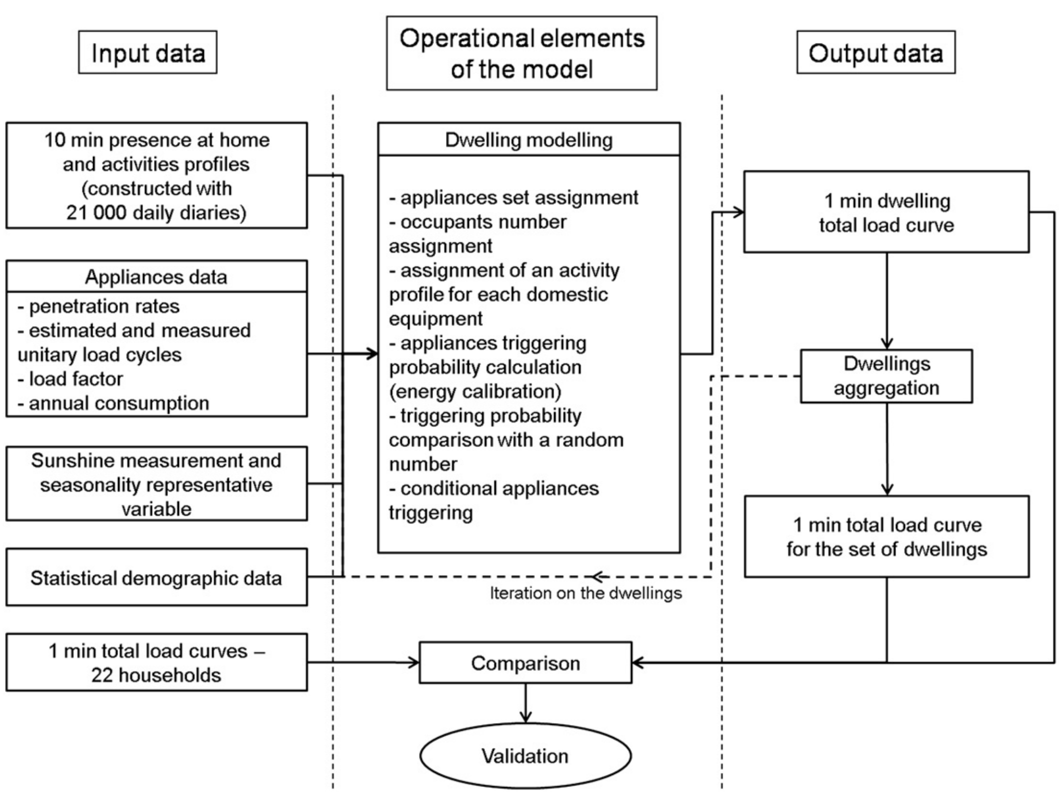

Fig. 13. Bloc diagram of Richardson et al.'s model [32].

corresponds to a single device (watching TV ⇔ television, 1-1 relation), other are more "ambiguous" (cleaning ⇔ ?, 1-n link). However, the last case does not mean that when carrying out an activity linked with n electric devices, all n appliances are turned on as long as the activity is conducted. It only allows a possible simultaneous use of the same activity related appliances.

"Other activities" related appliances have been put together by the authors because:

- either any of the other activity profiles did not match with them (e.g. telephone). Thus they are only dependent on the human presence at home,
- or their functioning is continuous (e.g. cold appliances) and their modelling is not function of the availability at home,
- or finally their use is much more linked with an exogenous parameter such as the outer temperature what is the case of heating.

When simulating a sample of households, their set of domestic appliances has been randomly assigned with respect of the national penetration rates (multi-equipment is taken into account). During a simulation, an electric device can be in two different states: turned on and turned off. For some appliances, last state imply a standby consumption which is taken into consideration in the load curve modelling. Moreover, in Richardson et al.'s opinion, sharing of equipment and use of linked devices (e.g. washing-machine/tumble-dryer) can be "read" directly from the time of use data that have been arranged in the adequate form to serve as input of the model.

To calculate a load curve at each time point, four steps are required:

1. according to the selected appliance, the number of active people at the simulated time step and the type of the day, the corresponding daily activity profile is chosen;
2. the calculated time point value is read on the activity profile;
3. then the device starting probability has to be calculated. It is done by multiplying the value obtained in step 2 with a scalar factor. In fact, this last figure ensures the energy accuracy of the model because it relies on the mean annual number of uses for each equipment (device energy consumption/mean energy consumption per cycle);
4. finally, the device launching probability is compared to a random number generated thanks to a [0; 1] uniform density function. If the probably is greater than the random number, the appliance is launched.

In order to validate the results of their model, Richardson et al. conducted an in-depth multi-criteria study. Comparisons have been carried out considering following aspects:

- annual and mean daily energy consumption;
- daily load curves;
- 1 min power demand volatility;
- diversity of the power demand;
- load duration curve;
- load factor.

As reference data, Richardson et al. make use of 1 min load curves measured in 22 dwellings. These data are totally independent of the values that serve as model inputs.

As reference data, Richardson et al. make use of 1 min load curves measured in a sample of 22 dwellings located in the East Midlands area. These validation data are totally independent of the values that serve as model inputs.

The followings points sum up the main conclusions made by the authors:

- electric heating has been excluded from the validation study because of a too low penetration rate;
- one year simulation for 22 households shows that calculated energy consumption matched well with the validation data in average but its standard deviation was less than the real one. Assumptions of the model and input data biases can be the causes;
- in terms of average daily consumption, inter-month variations are correctly modelled but seasonality influence is under-evaluated. Lack of precision in the diaries and non modelling of the heating auxiliaries can explain this observation;
- when considering the mean daily calculated load curve, the model under-estimates power demand during the night and the morning peak occurs later than in the reality. The fact that the measured households sample does not match the national case can be responsible for this difference;
- the model shows a little ability to represent little and large power demand transitions.[14] To the authors' opinion, modelling simplifications are largely responsible for these observations;
- diversity factor and After Diversity Maximum Demand (ADMD) values from the model are close to the real indicators;
- load duration curves from reality and model are quite similar.

As a conclusion, Richardson et al.'s model provides high spatial and time resolution load curves thanks to detailed time of use data. Its strengths and weaknesses have been identified by the authors and mostly listed in the previous paragraphs. We would underline the unknown concerning the modelling of heating. In [32], Richardson et al. do not mention the use of a building simulation tool which seems to us necessary to build up a relevant load curve at a fine time step. Concerning the appliances modelling and more precisely the nominal power values of the equipments, only mean values have been used in the model. A statistical distribution can generate more variations and diversity between the simulated households. Moreover, the model is restricted to short-term forecasting because new end-uses cannot be integrated. Finally, households' socio-economic characteristics, price of energy and DSM measures are load curves influences that are not included in Richardson et al.'s model.

4. Statistical-engineering model: Train et al.'s model

Previous models either follow an upward (bottom-up) or downward (top-down) process that both present advantages and limits. From this assessment, the main motivation to develop an other kind of model is to put to use all benefits of each approach. That is what Train et al. [34] tried to do in building up a Statistical Adjusted Engineering (SAE) model.

The methodology corrects the end-use load curves simulated with an engineering approach (so outside the model) thanks to statistical coefficients obtained through measured load profiles. In terms of input data, Train et al. made notably use of a PG&E metering campaign [35] that provided them total and by end-use load curves for about 800 domestic clients. During this survey information concerning the households (income, dwelling size area, number of occupants, appliances penetration rates, etc.) has

[14] Transition = $|P(n+1)-P(n)|$ where P is the power demand value at the time step n.

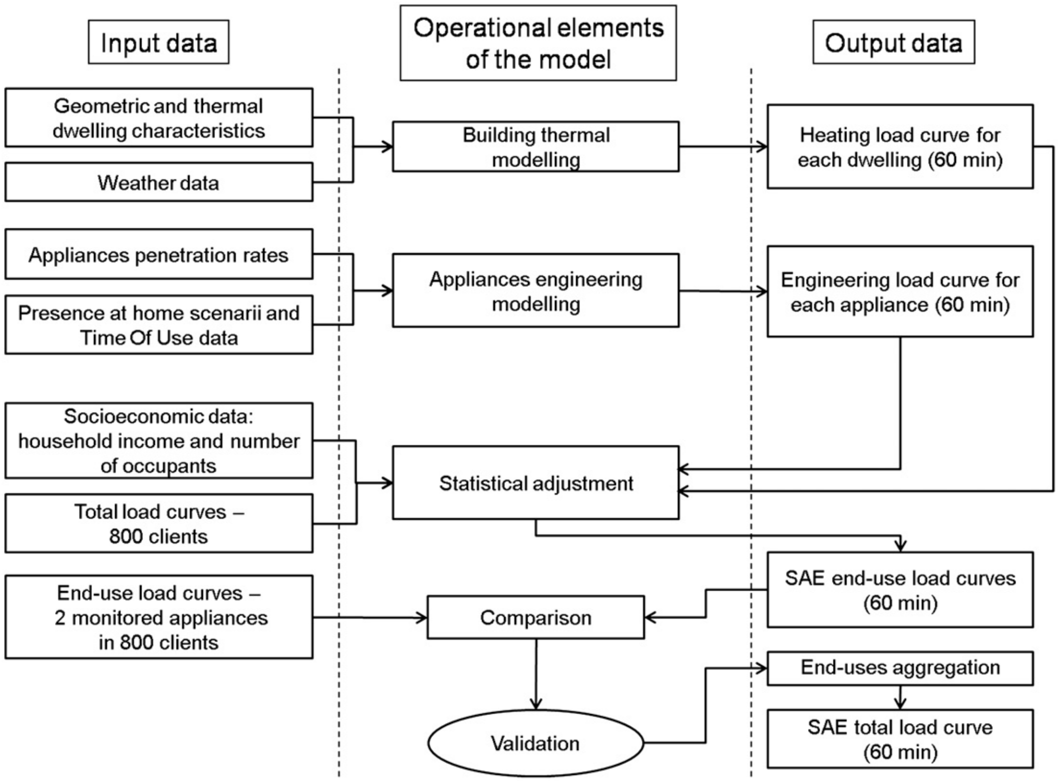

Fig. 14. Bloc diagram of Train et al.'s model [34].

been collected. Moreover engineering loads have been calculated by ADM Associates using the method described in [36].

Thus engineering power demand values correspond to the explanatory variables of a conditional demand model into which they are put. The general functioning of Train et al.'s model is shown under a bloc diagram in Fig. 14. Results are given at the 1 h time resolution.

As it is said in [35], statistical adjustments on load curves can occur at each time step (1 h), for each end-use i and/or for each customer j. However it does not seem to be relevant to adjust engineering load curves on these three sources of influence because it would totally "hide" the simulated part of the load curve results.

That is the reason why the authors constructed four SAE models with progressive adjustments. These are applied to one or several time periods l ($l \in [1;\tilde{l}]$) defined within the day on the one hand and to take into account the customers' characteristics on the other hand.

In the first defined SAE method, engineering load curves are adjusted with a correction factor zeta; that is specific for each end-use i (zeta; = zeta;(i)). Yet this coefficient is constant over the day (only one period is defined) and it does not take into account the customers' characteristics. In the second SAE model, these characteristics are taken into consideration for the adjustment of the load curves (zeta; = zeta;(i,j)). However, once again only one period is defined for the adjustment that is to say that zeta; is not time-dependent. In the third SAE approach, four periods l are defined and the adjustments are different according to the end-use and the period but without considering the customers' specificities (zeta; = zeta;(i,l)). Finally the last SAE model variant is the combination of model 2 and 3: engineering load curves are corrected according to the end-use i, the customer j and the period l (zeta; = zeta;(i,j,l)).

Whatever the adjustment level, Train et al.'s model is looking for estimating the total power demand of customer j at time t, $P_j(t)$, in rectifying the simulated power demand value at t for the end-use i of the customer j, $R_{i,j}(t)$,[15] thanks to the correction factor zeta;$_{i,j,l}$[16] and an error $u_j(t)$ according to Eq. (12).

$$P_j(t) = \sum_{i=1}^{n} \sum_{l=1}^{\tilde{l}} \text{zeta;}_{i,j,l} \cdot R_{i,j}(t) \cdot D_{i,j} + u_j(t) \tag{12}$$

In few words, the authors observe that different adjustment periods provide a better correction of the load curves calculated with engineering models. However, introducing demographic variables (customers' characteristics) in the model do not seem to be of great interest when considering the gain in terms of results accuracy.

A wider evaluation and validation work has been conducted by Train in [35]. This publication mentions an extended version of the fourth model (adjustment on nine periods, differentiation in terms of type of day, adaptation of the model according to the season summer/winter, etc.) but conceptually it is the same method than this explained above.

In the whole, the assessment of the model has lead to general conclusions that we previously mentioned as for instance the limits of the engineering models to take into account the time of use and the regulation of thermal appliances. On top of that, Train compared the SAE, engineering and measured daily load curves

[15] n end-uses are considered – a dummy variable $D_{i,j}$ indicates the presence or the absence of each of them in the customers' homes.

[16] That depends on the end-use i and/or the consumer j and/or the adjustment period l according to the SAE model variant.

Table 2
Reading grid (first part) of the studied load curve reconstitution models.

Type of model	Authors [Publication] Purpose of the model	Inputs of the model	Outputs of the model	Modelled end-uses	Nature of the generated behavioural diversity	Model validation
Deterministic statistical disaggregation (top-down) models	Aigner et al. [10] To get end-uses load curves without monitoring	Assumptions concerning the non functioning of a series of equipments at certain hours within the day Measured daily load curves at the household level	Daily load curves returned at a 60 min time step for nine domestic appliances at the household level	Specific electricity appliances, heating, cooling, DHW	Deterministic	No validation
	Bartels et al. [12] Simulation of the impact of various scenarii on the load curve at the regional level Decision support for the planning of the capacities of the utilities	Evolution scenarii concerning technological aspect, socio-economical aspect, appliances penetration rates, number of customers Measured daily load curves at the household level	Daily load curves per appliance returned at a 60 min time step for the regional residential class considered. The load curves are calculated according to a scenario (worked day or not worked day for a selected month)	Specific electricity appliances, heating, cooling, DHW	Deterministic	On total load curves
Statistical random bottom-up model	Yao and Steemers [14] Support for the design of energy systems including renewables Support for the prediction of the load curve for a selected community	Occupation scenarii Statistical daily consumptions by end-use and appliance	Daily multi end-uses load curves returned at a 1, 5, 15 or 30 min time step corresponding to, from a single household, to an entire community	Specific electricity appliances, heating, DHW	Mathematical random	On total load curves
Time of use based bottom-up models	Walker and Pokoski [23] Prediction of the load curve as support for the planification of new power generation capacities	Occupation, activities and end-use scenarii Unitary load cycles (from modelling and apparently from measures)	Daily load curves returned at a 15 min time step for a household (or a sample of households) that is specified with taking into account of the psychological and behavioural influences	Specific electricity appliances, DHW	Scenario based probability	On total load curves
	Capasso et al. [25] Support for the utilities for the evaluation of power management measures and DSM policies	Occupation and activities scenarii Constructed unitary load cycles Consumption available at the household level (with an ambiguous temporal restitution of these data) Statistical mean annual consumption per appliance (from measures but with an ambiguous temporal restitution of these data)	Residential daily load curve returned at a 15 min time step for a geographical area thanks to the synthesis of multi end-uses load curves at the household level	Specific electricity appliances	Scenario based probability	On total load curves
	Armstrong et al. [29] To get electricity consumption profiles for the modelling of micro-cogeneration devices	Occupation and activities scenarii Measured and constructed unitary load cycles Mean annual consumption available at the household level Mean annual consumption of the appliances	Daily load curve for electricity specific appliances returned at a 5 min step for typical households	Specific electricity appliances	Scenario based probability	On reconstructed load curves for specific electricity appliances

Table 3
Reading grid (second part) of the studied load curve reconstitution models.

Type of model	Authors [Publication] Purpose of the model	Inputs of the model	Outputs of the model	Modelled end-uses	Nature of the generated behavioural diversity	Model validation
Time of use based bottom-up models	Widén et al. [26]	Occupation and activities scenarii	Daily load curves returned at a 5–60 min time step and DHW draw profiles (ambiguous temporality) at the occupant level. Aggregation of previous results to get those corresponding to a household or a little community	Specific electricity appliances, DHW	Scenario based determinism	On load curves per end-use
	Determination of the households' energy consumption Evaluation of future changes (modifications of the behaviour, energy efficiency improvement) that impact on the electricity use	Constructed unitary load cycles				On DHW draw profiles On total load curves On daily electricity consumption per end-use On yearly consumption for DHW
	Widén and Wäckelgård [30]	Occupation and activities scenarii	Daily load curves returned at a 1–60 min time step for a household and possible aggregation to get results at a larger scale	Specific electricity appliances	Scenario based probability	On total load curves
	Support for studies on electricity production at the household level	Measured daily load curves per appliance Constructed unitary load cycles				On the household's yearly consumption On yearly consumption per end-use
	Richardson et al. [32]	Occupation and activities scenarii	Daily load curves returned at a 1 min time step for a household and possible aggregation for a set of households	Specific electricity appliances, heating, DHW	Scenario based probability	On total load curves
	To anticipate the impact of "low carbon" measures on the load curve of a local distribution network	Measured unitary load cycles Statistical yearly consumptions per appliance based on studies				
Probabilistic empirical bottom-up models	Stokes [17]	Daily load curves measured at the household level	Daily load curves returned at a 1 min and 30 min time step for respectively a specified and "mean" household and possible aggregation at a community scale	Specific electricity appliances, heating, DHW	Empirical probability	On total load curves
	Evaluation of the impact of the decentralized electricity production in the case of a low voltage network	Daily load curves measured at the appliance level Unitary load cycles constructed from measures Yearly consumptions per end-use coming from surveys				
	Paatero and Lund [21]	Daily load curves measured at the household level	Daily load curve at a 60 min time step for a household and possible aggregation at a larger scale (thousands of households)	Specific electricity appliances	Empirical probability	On total load curves
	To get accurate domestic electricity consumption data to identify the impact of DSM measures	Unitary load cycles constructed from measures Daily consumptions measured at the household level				On household's yearly consumption

Table 3 (*continued*)

Type of model	Authors [Publication] Purpose of the model	Inputs of the model	Outputs of the model	Modelled end-uses	Nature of the generated behavioural diversity	Model validation
		Consumptions per appliance in proportion with the dwelling consumption (data from studies without a precise temporality)				
Hybrid model (statistical-engineering)	Train et al. [34] To take advantage of the statistical and the engineering models to obtain end-uses load curves	Measured daily load curves available at the household level Appliances daily load curves from modelling	Daily load curves returned at a 60 min time step per appliance and for a specified household (or a group of households)	Specific electricity appliances, heating, cooling, DHW	Statistical	On total load curves

with help of the statistic S defined in Eq. (13).

$$S = \frac{\sqrt{\sum_{t=1}^{24} (L(t) - M(t))^2}}{\sum_{t=1}^{24} \frac{M(t)}{24}} \cdot 24 \tag{13}$$

where $L(t)$ and $M(t)$ are the 1 h power demand value averaged on the sample of simulated customers that is obtained by the SAE (or the engineering) method and measured respectively. In fact, this is the square root of the *NVF* that we previously have met.

More precisely, Train focused his assessment on the comparison between SAE and engineering loads in order to quantify the impact (improvement and/or deterioration according to the considered end-use) of the statistical adjustment. The conclusion of the author is that the SAE model improves the engineering results if and only if physical models do not integrate empirical knowledge (so from measures) or the structure and/or the size of the sample used for the adjustment is (are) not optimal in terms of representativeness.

To conclude, Train et al. developed an hybrid model that takes advantage of the traditional load curve modelling techniques. Measured load curves calibrate power demand profiles obtained by engineering models. On top of that, this method allows to get round the diversity modelling because it is contained in the adjustment coefficients.

However this approach is only relevant for short term forecasting because it reproduces past power demand profiles what is the case of some other models. Changes and evolutions in the housing stock cannot be implemented and simulated in this model. On top of that, the miscellaneous category encompasses a lot of equipments. The corresponding load curve can be well estimated in the whole but what about each of the appliance in this field?

5. Cross analysis

In this section, the authors sum up and compare the models of the literature that were described in the previous paragraphs. First of all, a general overview of them is given under a table form. This contains the in-our-opinion most important criteria that characterize a load curve reconstitution methodology. Then certain comparisons are proceeded with focusing on the advantages and the limits of each methodology. Finally, we plot the results of this cross analysis through a "pseudo 3D" representation.

5.1. Reading grid

To construct this reading grid, we began to list the to-our-mind most relevant characteristics for defining a load curve reconstitution model: these criteria correspond to the columns of the table and the models are arranged in rows.

Then we completed each cell of the table thanks to a restricted number of modes so as to facilitate the reading. This way we obtained Tables 2 and 3.

5.2. Focused comparisons

5.2.1. Modelling the diversity

As we previously said, estimating the electric power demand for the domestic sector implies the modelling of the diversity. The above descriptions of the methodologies show that various strategies have been developed by the authors to represent it. Some of the models only "catch" the diversity directly from the input data without clarifying it. Other models generate it totally or partially thanks to more or less elaborated random processes

(probability distribution functions, Monte Carlo extractions, Markov chains, etc.) or statistical approaches (correction factors).

When only considering the models that represent the diversity, Walker and Pokoski's work is the to-our-knowledge first one which separately takes into account the presence at home of the households' members on the one hand (necessary but not sufficient condition to reconstruct the domestic load curve) and the proclivity for carrying out certain domestic activities (or using appliance(s)) on the other. On top of that and like the models of Capasso et al. [25], Widén et al. [26], Widén & Wäckelgård [30] and Richardson et al. [32], each household's member is characterized such a way. This constitutes a real modelling refinement.

However, in order to feed models that follow such an approach, precise information have to be available. Among other data, the authors made use of time of use surveys which are only representative of a selected households sample at a certain time. In order to ensure the representativeness of the models using TOU data, these must be periodically updated which supposes permanent and so expensive studies.

In some models, a consumer mean behaviour has been defined and applied to the simulated number of dwellings. Here is open the question of the likelihood of this construction because a mean consumer only has sense with regard to one of its characteristics or some of them. As the behaviour is influenced by too many parameters, defining a realistic mean one does not seem relevant.

For energy purposes, building up a mean consumer is viable because it is possible to calculate the mean consumption of a consumer sample over a certain duration: the mean consumer is the one who uses the calculated average energy consumption.

In terms of power demand, a mean consumer has no sense; because of the diversity in a customers sample, that among other things comes from behavioural and technical influences, there is every chance that nobody has the same load curve as the After Diversity Mean Load Curve (ADMLC). It is calculated by addition of each individual load curve and then division by the number of aggregated consumers. However what can be defined with regard to the considered sample is the marginal consumer that is to say the consumer that will be added to the original sample. Its most likely representative load curve would be the ADMLC.

Another possibility to model the diversity through the human behaviour is to calculate from input data transition probabilities from a domestic activity to another one, and this, for all activities. When integrating this within a Markov Chain, a random influence completes the variety that is already contained in the input data. However the link between the activities and the use of appliances remains to be set up what is not trivial.

To our opinion, it is possible to set a framework for the modelling of the diversity that can be less dependent on the input data. With help of a sufficient knowledge of the simulated housing stock, logic rules and constraints can be defined and applied in order to generate diversity.

5.2.2. *Allocation of appliances functioning cycles within a simulated day*

Different approaches exist in order to construct scenarii that define the use of appliances at the daily level.

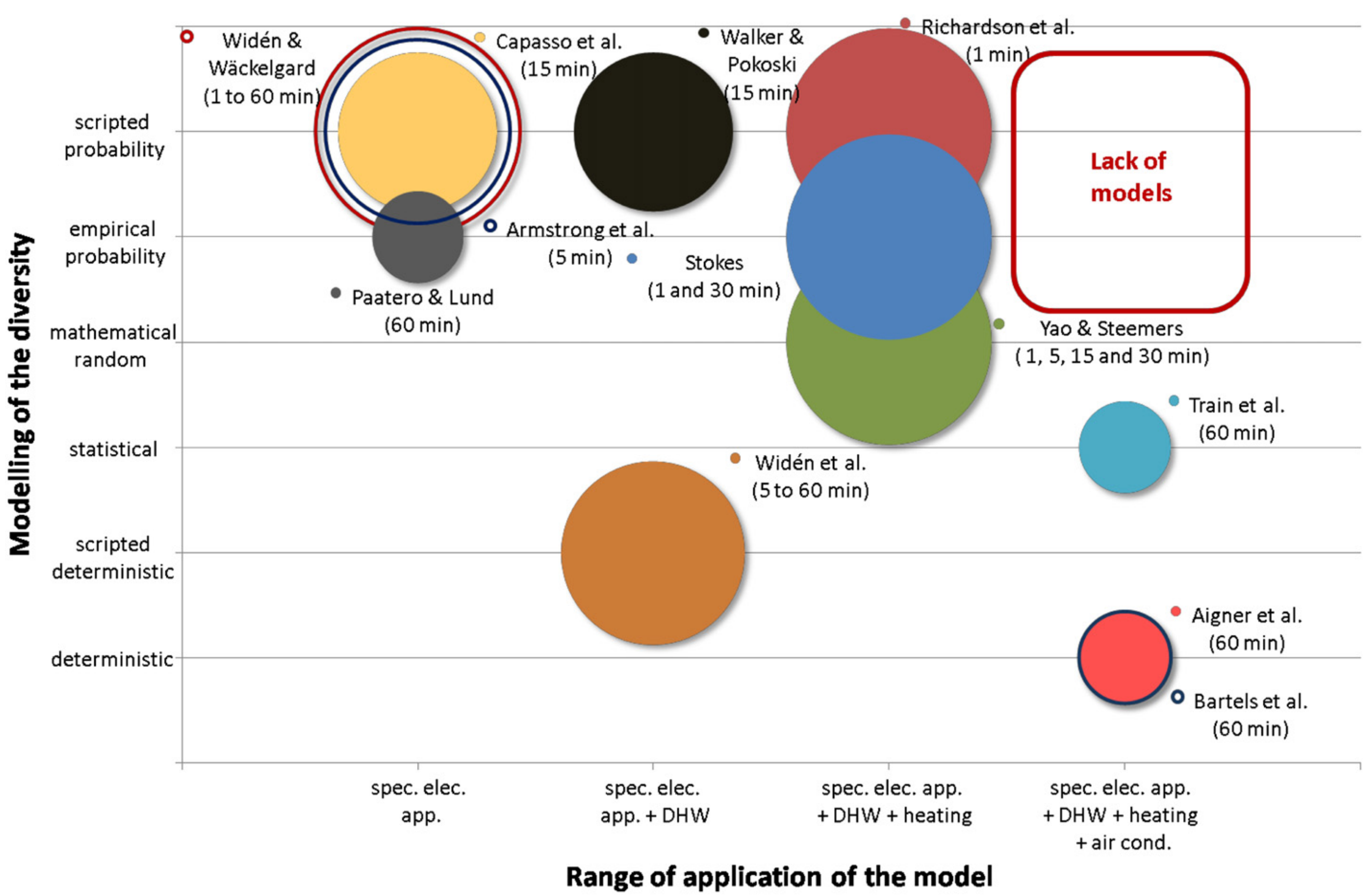

Fig. 15. Cross analysis diagram of the load curve models.

The first one is to calculate an end-use average daily or weekly consumption from annual consumption figures and to launch a corresponding number of appliances cycles according to the unitary consumption of each end-use. However, this method can lead to an unrealistic daily usage of each appliance as for instance a $\frac{3}{4}$ washing-machine cycle to launch each day.

The second one is to make use of the daily end-uses (or domestic activities) probability distribution functions constructed thanks to time of use data. In order to reach the energy consumption target, the number of end-uses starts must be controlled. This way is limited in the sense that in the better case it reproduces one measured reality and is representative of it. Changes in the end-use behaviour can not be simulated.

To our mind, we think that a method based on the knowledge of appliances use frequencies at different time scales can be more realistic than the previous ones. It will rely on the definition of types of day and households. When considering the week as the modelling framework, the sequential distribution of the launching of end-uses cycles for each day will take into account these influences but also the household's availability at home duration and the number of end-uses cycles already started in the considered week. On top of that, it would be necessary to constitute some links between appliances in order to improve the realism of simulations. For instance, the use of tumble-dryer is connected to the use of washing-machine. Moreover, it will be required to construct an end-uses ranking for each simulated day so as to launch them according to a priority order.

5.3. Positioning the models on a pseudo 3D plot

As we said in the introduction, we decided to represent on a chart the positioning of the models. In order to facilitate the reading of the representation, we restricted the number of regarded criteria: thus we only considered the range of application of the model (so the simulated appliances), the way the model (re)constructs the diversity and finally its time resolution.

In Fig. 15, the models are represented by bubbles whose diameters are inversely proportional to their time resolution. That is to say that a big bubble corresponds to a model that provides load curves with a fine time accuracy.

In the north-east corner of Fig. 15, a lack of models is noticeable: to our knowledge, there is no model that simultaneously provides load curves for all domestic appliances (inclusive thermal ones), at a fine time scale and with an advanced methodology to represent the diversity.

6. Conclusion

In this paper, we review 12 domestic load curve models. In the first part, we adopted a systematic analysis of each of them with focus on the finality of the model, its inputs/outputs, the modelled end-uses, the way diversity is taken into account and finally what kind of validation has been carried out. On top of that we built-up a synthetic block-diagram of each approach. In the second part of the paper, we considered them together carrying out a transverse analysis. A reading grid and a pseudo 3D plot was established at the end of the review.

This work has been voluntarily limited to a little number of models because of the willingness to analyse each of them in details. Other existing techniques for the load curve modelling, such as neural networks or agent-based method, have not been dealt with in this review. Further research has to be carried out to list, evaluate and analyse all possible methodologies for the reconstitution of the residential load curve. This purpose seems to us of great importance because of the undergoing radical transformation of the dwellings, domestic end-uses and human habits and behaviour.

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